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Degree Ph.D. Program Administration–Health Services

Name of Candidate Glenn A. Yap

Committee Chair Jeffrey R. Burkhardt

Title Staffing Levels and Inpatient Outcomes at Military Health Care Facilities: A Resource-Based View

Using a Resource-Based Theory/View of the firm, this study examined if increased inpatient staffing levels at military hospitals can generate a competitive advantage based on better patient quality outcomes. Specifically, this study examined the relationships between levels of registered nurse staffing, nonregistered nurse staffing, and physician staffing to patient quality outcomes. Patient quality outcomes in this study were measured by average length of stay, in-house mortality rates, and 30-day readmission rates. The current study found some support that increasing nurse staffing, especially registered nurse staffing, does lead to better inpatient quality outcomes as defined by shorter average length of stay and lower inpatient mortality rates.

DEDICATION

To my wife Aranka and my two sons Jonathan and Alexander. You are what gives meaning to life and make life worth living. You always gave me the inspiration and motivation to complete this dissertation. I have truly been blessed.

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STAFFING LEVELS AND INPATIENT OUTCOMES AT MILITARY HEALTH CARE FACILITIES: A RESOURCE-BASED VIEW

by

GLENN A. YAP

A DISSERTATION

Submitted to the graduate faculty of The University of Alabama at Birmingham,
in partial fulfillment of the requirements for the degree of
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LIST OF ABBREVIATIONS

ALOS	average length of stay
BSC	balanced scorecard
DoD	Department of Defense
DRG	diagnosis related group
EAS IV	Expense Assignment System Version 4
FTE	full-time equivalent
ICU	intensive care unit
LOS	length of stay
M2	Military Health System Mart
MDG	major diagnostic group
NHS	National Health Service
n	sample size
Non-RN	nonregistered nursing
OBD	occupied bed day
RBV	resource-based view/theory of the firm
RN	registered nurse
RWP	relative weighted product
SIDR	standard inpatient data record

CHAPTER 1: INTRODUCTION

Background of the Problem

Hospitals must constantly balance cost, quality, and access. The Balanced Budget Act and Ambulatory Payment Classifications system are decreasing resources available to hospitals (Kerfoot, 2000). At the same time, hospital payroll costs grew by 8.6% in 2001, more than twice the rate from the previous year (Bureau of Labor Statistics, 2002). Wages and benefits account for about 57% of all hospital costs. Nurses account for an estimated 63% of a hospital's labor costs (PriceWaterhouseCoopers, 2003). Given these facts, it is not surprising that, when hospitals look to reduce overall costs, labor, and especially nurse labor, is closely examined. The Advisory Board Company (1999) described nurse executives in the "line of fire" because they are taking the brunt of the cost cutting activities and, at the same time, being challenged to improve patient outcomes.

The military hospitals that the Department of Defense (DoD) is responsible for face the same challenges as their civilian counterparts. Two key differences between military and civilian hospitals exist. First, military hospitals have both peacetime and wartime missions. Although a significant amount of time is spent providing peacetime health care to military beneficiaries, military personnel must also spend time training for wartime readiness activities. Second, all physicians in military hospitals are salaried employees of the hospital. Although this can occur in the civilian arena, it is much less common. Therefore, labor costs at military hospitals tend to be a larger portion of the overall hospital budget compared to civilian hospitals.

As such, the challenge for both civilian and military hospitals is to develop and implement strategies for success. Aharoni (1993) defined strategy as an attempt by a firm to achieve and sustain competitive advantage over other firms. This role of competitive advantage may have been derived from the economic and militaristic origins of the strategy literature (Whittington, 1993). A body of empirical literature showed the importance of firm-specific factors in explaining variations in economic rent (Jacobsen, 1988; Hansen and Wernerfelt, 1989). Short, Palmer, and Ketchen (2002) found that both organizational resources and membership in a strategic group were significantly related to performance. Cool and Schendel (1988) found significant and systematic performance differences among firms belonging to the same strategic group within the U.S. pharmaceutical industry. Rumelt (1991) found that business units differ far more within than across industries.

The resource-based view/theory of the firm (RBV) has emerged in recent years as a popular theory of competitive advantage (Fahy, 2000). It has become one of the standard theories in strategy and is the dominant theory in the explanation of interfirm performance differences (Hoopes, Madsen, and Walker, 2003). RBV starts with the assumption that managers devote their efforts, or make strategic choices, to generate a sustainable competitive advantage through the accumulation and deployment of strategic assets (Barney, 1991; Amit and Schoemaker, 1993; Short *et al.*, 2002). These competitive advantages subsequently allow them to achieve superior performance (Peteraf, 1993). Superior performance in RBV has been defined traditionally as being able to earn extraordinary rents. The most common definition of rents is Ricardian rents. Ricardian rents are extraordinary profits earned from resources that are in fixed or limited supply (Amit and Schoemaker, 1993).

Scholars argue that resources form the basis of firm strategies and are also critical in implementation of those strategies (Schoenecker and Cooper, 1998). Firm resources and strategy interact to produce positive returns (Hitt, Bierman, Shimizu, and Kochhar, 2001). Therefore, the RBV perspective attempts to explain how a firm's resources, which are related to its strategy, impact its subsequent performance (Wernerfelt, 1984; Barney, 1986a; Hatten and Hatten, 1987; Mosakowski, 1993; Noda and Collis, 2001).

Porter (1980) stated that firms use three generic strategies to compete successfully: cost leadership, differentiation, and focus. Early studies of hospital competition showed that hospitals did not compete on price but on availability and sophistication of services (Salkever, 1978). It was assumed that having more sophisticated services available also meant better quality care. Today's hospital market is not much different. Morrisey (2001) stated, as a result of conventional health insurance, consumers have been shielded from the true cost of health care. Therefore, the decision to use care is based on services, amenities, and quality of the provider. One should expect that hospitals would compete based on these factors (Morrisey, 2001). Other studies have also supported the idea that hospitals compete on the basis of quality (Luft, Robinson, Garnick, Maerki, and McPhee, 1986; Woolley and Frech, 1988-1989; Calem and Rizzo, 1995), implying hospitals may be employing the differentiation strategy to compete.

For hospital managers, the challenge is to identify, develop, protect, and deploy resources and capabilities in a way that provides the firm with a sustainable competitive advantage and, thereby a superior return on capital (Amit and Schoemaker, 1993). Because human labor, especially nursing labor, accounts for a large proportion of a typical hospital's budget, it would be logical to expect that hospital managers must devote time to identify, develop, protect, and deploy their human capital. Only one study, as far as can

be determined by this author, has applied and tested the RBV theory to hospitals in the strategic management literature (Short *et al.*, 2002). There have only been a relatively small number of other empirical tests of RBV. In addition to hospitals, RBV has been tested in the manufacturing industry (Robins and Wiersema, 1995; Schroeder, Bates, and Juntilla, 2002), law firms (Hitt *et al.*, 2001), liberal arts colleges (Kraatz and Zajac, 2001), Dutch audit industry (Maijoor and van Witteloostuijn, 1996; Pennings, Lee, and van Witteloostuijn, 1998), the integration of environmental issues into firms' strategic planning (Judge and Douglas, 1998), Hollywood film studios (Miller and Shamsie, 1996), the U.S. banking industry (Mehra, 1996), companies in the northeastern United States (Powell, 1995), U.S. and European pharmaceutical industries (Henderson and Cockburn, 1994), the U.S. foreign auto industry (Tallman, 1991), the global bearings industry (Collis, 1991), and on 60 Fortune 1000 firms (Hansen and Wernerfelt, 1989). Most of these studies, including the test using hospitals, have supported positive, direct effects of resources on performance (Hitt *et al.*, 2001). The nursing and medical literature contain studies that suggest which hospital assets may potentially be strategic assets and how these assets are potentially deployed to allow a hospital to generate a sustained competitive advantage.

Significance of the Study

This study will attempt to add to the strategic management literature by adding to the very limited existing literature applying and testing the RBV in hospitals and concentrating on inpatient physician and nursing services resources. Short *et al.* (2002) stated their study only used a limited set of resources, and this limitation suggests that many research opportunities are available in discovering what types of hospital resources lead to

competitive advantage. Second, this study will expand the body of literature that examines the relationship between nursing staff and patient outcomes and between physician staffing and patient outcomes. Because none of the nursing and medical studies that are "related" to RBV have used hospitals in the military setting, this proposed study will also add to these streams of literature.

Finally, results from this study have larger potential implications. If the proposed study does not find any significant relationships, each Service (U.S. Air Force, U.S. Army, and U.S. Navy) should seriously reexamine their resource allocation policies among their health care facilities. The Services may be able to reduce the staffing levels at facilities that may be "overstaffed" without reducing operating efficiency or effectiveness. Although there is some cooperation between Services in providing health care to the military beneficiary population, each Service operates its own system of hospitals and clinics. If significant relationships are found as hypothesized, again the Services should reconsider how they currently allocate and deploy staff in their medical facilities. The Services may need to examine how to increase staffing levels at facilities that are "understaffed" to improve operational results. It is hoped that the results of the proposed study will lead to more efficient and effective care being delivered to the military population. The sample consists of all 75 DoD inpatient health care facilities in operation during the period from October 1, 2001, to September 31, 2002 (DoD's fiscal year). The relevant research questions are as follows:

1. Do military health care facilities that provide more total nursing full-time equivalents (FTEs) to care for inpatients experience better patient outcomes?
2. Do military health care facilities that provide more registered nurse FTEs to care for inpatients experience better patient outcomes?

3. Do military health care facilities that provide more nonregistered nurse (non-RN) support staff FTEs to care for inpatients experience better patient outcomes?
4. Does the level of non-RN support staff moderate the relationship of registered nurse (RN) staff levels on inpatient outcomes?
5. Do military health care facilities that provide more physician FTEs to care for inpatients experience better patient outcomes?
6. Does patient length of stay directly affect and mediate the impact of staffing resources on other patient outcomes?

Summary

Now and in the foreseeable future hospitals will most likely try to create a sustainable competitive advantage by increasing the quality of patient care provided (Luft *et al.*, 1986; Woolley and Frech, 1988-1989; Calem and Rizzo, 1995; Morrisey, 2001). On the other side, hospitals must also be concerned with the cost of providing quality health care. Because labor costs, especially nursing, comprise the largest portion of a hospital's budget (PriceWaterhouseCoopers, 2003), hospitals trying to reduce costs must always consider reductions in hospital staffing.

This study is concerned with investigating the relationship between hospital staffing and quality hospital inpatient outcomes. Specifically, registered nurses, nonregistered nursing staff, and physician staffing will be examined. Based on the idea that internal resources may be the only means of creating sustainable competitive advantage (Dierickx and Cool, 1989; Barney, 1991; Amit and Schoemaker, 1993), RBV suggests that hospital labor is one internal hospital resource critical to generating this type of advantage through the provision of high quality patient care. RBV will be used as a frame-

work to show whether a hospital executive's strategic choices in the allocation of limited resources lead to the generation of better quality patient care and eventually a sustainable competitive advantage.

CHAPTER 2: LITERATURE REVIEW

This chapter provides a comprehensive review of the theoretical background and empirical investigations in the relationship between resources and performance in both the hospital and nonhospital industries. The lack of studies that apply RBV to the health care setting made reviewing the RBV literature in the nonhealth care setting very important, even though researchers have questioned the straightforward application of research frameworks developed in the broader strategic management literature to the health care industry due to the belief that the health care industry has unique characteristics (Fottler, 1987; Luke, Begun, and Pointer, 1989). The review of this body of literature will also aid in the development of an externally valid theoretical research framework used in this study. This chapter will first cover RBV and will then proceed to cover hospital inpatient performance outcomes literature and finally the nursing and medical research streams that examined the relationship of resources to outcomes.

Resource Based View/Theory

Until the late 1980s, RBV was characterized by a fragmented process of development (Fahy, 2000). Even thought the term RBV was first used by Wernerfelt in 1984 (Wernerfelt, 1984), the earliest acknowledgement of the potential of firm-specific resources was found in the work of economists such as Chamberlain and Robinson in the 1930s; however, Penrose (1959) was credited for further developing this concept (Fahy, 2000). Chamberlain (1933) focused on firm heterogeneity and identified some of the key

capabilities of the firm as technical know-how, reputation, brand awareness, ability of managers to work together, patents, and trademarks. RBV places its primary emphasis on economic exchange (as opposed to social or political) and assumes organizational actors are rational beings that make decisions that maximize their self-interests. The basic assumption of this view is that "resource bundles" used to create and distribute services by firms are unevenly developed, giving rise to heterogeneous firms, which explains to some extent the ability of each organization to compete effectively (Ginter, Swayne, and Duncan, 2002). A central element of RBV is the presumptive connection between sustainable competitive advantage and the generation of economic rent (Lippman and Rumelt, 2003). Therefore, the resource view holds that the type, magnitude, and nature of a firm's resources and capabilities are important determinants of its profitability (Amit and Schoemaker, 1993).

Next, basic concepts in RBV will be defined: resources, capabilities, strategic factor markets, strategic assets, sustained competitive advantage, and superior performance (economic rents).

Resources

There have been many definitions given for resources. In the language of traditional strategic analysis, firm resources are strengths that firms can use to conceive of and implement their strategies (Learned, Christensen, Andrews, and Guth, 1969; Porter, 1980). Daft (2000) defined resources as all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm to conceive and implement strategies that improve its efficiency and effectiveness.

Firms that possess these resources are able to produce more economically and better satisfy customers (Peteraf, 1993). Amit and Schoemaker (1993) made a distinction between resources and capabilities. They defined resources as stocks of available factors that are owned and controlled by a firm. Makadok (2001) defined a resource as an observable asset that can be valued and traded, though it may be tangible or intangible. Ginter *et al.* (2002) defined resources as stocks of human and nonhuman factors, tangible and intangible, that are available for use in providing goods and services.

Resources a firm possesses that potentially can be used to generate a sustained competitive advantage have been categorized in many ways. Amit and Schoemaker (1993) stated that resources could be such things as knowledge and know-how (e.g., patents and licenses), financial assets, physical assets (e.g., property, plant, and equipment), or human capital. Barney (1991) classified resources into three categories: physical capital resources (Williamson, 1975), human capital resources (Becker, 1964), and organizational capital resources (Tomer, 1987). Physical capital resources are the physical technology used in a plant, the plant, equipment, and geographic location. Human capital resources are the training, experience, judgment, intelligence, and relationships of managers and workers in a firm. Organizational capital resources are a firm's formal reporting structure, planning and coordinating systems, and informal relations among groups within a firm and between a firm and those in its environment (Barney, 1991). Additionally, resources can be classified as tangible or intangible (Wernerfelt, 1984; Hitt *et al.*, 2001; Ginter *et al.*, 2002). Firms employ tangible resources such as buildings and financial resources and also intangible resources such as human capital, culture, and brand equity (Hitt *et al.*, 2001). As will be further discussed below, intangible assets are more likely to produce a competitive advantage because they are often rare and socially complex, thus

making them difficult to imitate (Itami, 1987; Barney, 1991; Peteraf, 1993; Black and Boal, 1994; Rao, 1994).

If firm resources are a source of competitive advantage, the first assumption must be made that firm resources may be somewhat heterogeneous and somewhat immobile. If this is not the case, no firm can obtain a sustained competitive advantage because all firms can obtain similar resources and implement similar strategies, improving effectiveness and efficiency equally, which would compete away any advantage (Barney, 1991). Barney and Hoskisson (1990) stated that it seemed reasonable to expect that most industries will be characterized by at least some degree of resource heterogeneity and immobility.

Capabilities

Capabilities refer to a firm's capacity to deploy resources, usually in combination, using organizational processes to affect a desired end (Amit and Schoemaker, 1993). Makadok (2001) argued that a capability was unobservable, intangible and unable to be valued and can only change ownership as part of an entire unit. In addition, it has also been argued that a capability can be valuable on its own or can enhance the value of a resource (Nelson and Winter, 1982; Teece, 1986; Tripsas, 1997). Organizational routines are an example of a firm's capabilities. One characteristic imputed to routines is the knowledge supporting the execution of the routine is tacit. The tacit nature of routines can potentially act as a mechanism to inhibit imitation by competitors (Itami, 1987; Rumelt, 1987; Knott, 2003). Contrary to this argument, Knott (2003) found that tacitness of routines did not act as an isolating mechanism to keep competitors from copying and thus giving it value in the quick print industry.

The dynamic capabilities perspective has extended RBV to the area of evolving capabilities (Hamel and Prahalad, 1994; Teece, Pisano, and Shuen, 1997; Miller, 2003). Teece *et al.* (1997: 516) defined dynamic capabilities as, "the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments." It has been argued that a firm can stay ahead of its competitors and earn superior economic rents by developing capabilities based on sequences of path-dependent learning (Dierickx and Cool, 1989; Teece *et al.*, 1997). Dynamic capabilities typically involve specialized resources and are long-term commitments (Winter, 2003). As a result, dynamic capabilities would be much more difficult and costly for rival firms to imitate and potentially give a firm a competitive advantage. Winter (2003) argued that it is not necessary for firms to develop dynamic capabilities to gain a competitive advantage. He reasoned that there is no guarantee that the cost of changing or developing new capabilities (hence the term dynamic) will lead to better performance. Changing environments can make the cost-benefit analysis of these new changes quickly shift from positive to negative (Winter, 2003).

Adner and Helfat's (2003) empirical study of the relationship between dynamic managerial capabilities and firm performance in the U.S. petroleum industry provided a direct test of the dynamic capabilities perspective. They defined dynamic managerial capabilities as "capabilities which managers build, integrate, and reconfigure organizational resources and competencies" (Adner and Helfat, 2003: 1012). Their study found that dynamic managerial capabilities were significant in explaining variance in firms' financial performances.

In the context of the health care environment, capability was defined as a "health care organization's ability to deploy resources and competencies, usually in combination,

to produce desired services" (Ginter *et al.*, 2002: 151). Among organizational capabilities that have been suggested as being sources for sustainable competitive advantage are organizational culture (Barney, 1986a; Fiol, 1991), organizational climate (Hansen and Wernerfelt, 1989), learning (Fiol and Lyles, 1985; Senge, 1990; Garvin, 1993), routines (Nelson and Winter, 1982; Hitt and Ireland, 1985; Mahoney and Pandian, 1992; Knott, 2003), administrative skills (Powell, 1992), process improvement (Stalk and Hout, 1990), and entrepreneurship (Schumpeter, 1934; Rumelt, 1987; Nelson, 1991). For purposes of this dissertation, Ginter *et al.*'s (2002) distinction between resources and capabilities and their definitions will be used.

Strategic Factor Markets

Barney (1986a) introduced the concept of a strategic factor market and defined it as a market where resources necessary to implement a firm's strategy are acquired. If strategic factor markets are perfectly competitive, then firms cannot achieve abnormal profits because the costs of obtaining strategic resources will approximately equal the economic value of those resources once they are used to implement product market strategies (Barney, 1986a). It is when imperfect competition exists in strategic factor markets that allows firms to earn above normal profits (economic rents). Barney (1986a) argued that differences in firms' expectations are a source of strategic factor market imperfections. If a firm's expectations of the value of the potential implementation of a strategy (through the acquisition of specific resources) is more accurate than a competing firm, the more accurate firm will more likely obtain resources for less than its economic value, avoid overpaying, and thus generate above normal returns (Barney, 1986a). A firm's view of the value of a resource arises from idiosyncratic information and capabili-

ties a firm possesses. The more distinctive this view, the more likely valuable opportunities will arise that are not seen by a firm's rivals (Denrell, Fang, and Winter, 2003). Other potential sources of strategic factor market imperfections are when a small number of firms already control the resources necessary to implement a strategy (Thompson and Strickland, 1980), when only a few firms have the financial backing to enter a strategic factor market (Barney, 1986a), and when firms do not behave in profit maximizing ways (Porter, 1980). These considerations imply that markets for strategic resources are highly imperfect, and the ability to purchase resources below their economic value to generate abnormal profits do exist (Denrell *et al.*, 2003).

Strategic Assets

Not all of a firm's resources, physical, human, and organizational capital, are strategically relevant resources that have the potential to generate a sustained competitive advantage for a firm (Barney, 1991). A firm's resources and capabilities that have the potential to give a firm a sustained competitive advantage and thus earn rents are also known as strategic assets (Amit and Schoemaker, 1993). Others have labeled these resources and capabilities as distinctive competencies (Selznick, 1957; Reed and DeFillippi, 1990; Fiol, 1991), core competencies (Prahalad and Hamel, 1990), firm specific competencies (Pavitt, 1991), and organizational capabilities (Ulrich and Lake, 1990; Stalk, Evans, and Schulman, 1992). Barney (1991) proposed that resources must have four attributes to potentially generate a sustained competitive advantage. They must be valuable, rare, and imperfectly imitable and have no strategically equivalent substitutes that are themselves either not rare or imitable.

Characteristics of Strategic Assets

Valuable. First, a resource is valuable when it enables a firm to conceive of or implement strategies that improve its efficiency or effectiveness. Although environmental models of competitive advantage isolate firm attributes that can exploit opportunities and/or neutralize threats, the resource-based model suggests what additional characteristics these resources must have if they are to generate a sustained competitive advantage (Barney, 1991). Peteraf and Bergen (2003) argued that the value of a resource is derived from its application in product markets, such as the satisfaction of consumer needs.

Rarity. Second, Barney (1991) stated that determining how rare a resource must be to have the potential of generating a competitive advantage is a difficult question. In general, as long as the number of firms that possess a particular valuable resource (or resource bundle) is less than the number of firms needed to generate perfect competition dynamics in an industry (Hirshliefer, 1980), that resource is considered rare and has the potential of generating a competitive advantage (Barney, 1991). Hoopes *et al.* (2003) argued that rareness is important only if it is valuable and cannot be imitated by competitors. They believed that concentrating on value and inimitability lies at the heart of RBV. Peteraf and Bergen (2003) argued that the rarity, or scarcity, of a resource should be assessed in terms of its functionality versus resource type. If perfect substitutes are available, the rarity of a resource type is not important.

Imitability. The third attribute a resource must possess for it to potentially generate a sustained competitive advantage is that it must also be imperfectly imitable (Rumelt, 1982; Barney 1986a, 1986b). A resource can be imperfectly imitable in one or a combi-

nation of three ways: dependent on historical conditions, causally ambiguous, or socially complex (Barney, 1991). Hoopes *et al.* (2003) argued that three isolating mechanisms prevent resources and capabilities from being imitated: property rights, learning and development costs, and causal ambiguity. Barney's (1991) conditions for a resource or capability to be imperfectly imitable will be discussed first.

The ability of a firm to obtain a resource may be dependent upon unique historical conditions. This approach asserts that a firm's ability to acquire and exploit some resources depends upon its place in time and space (Barney, 1991). For example, a firm's unique and valuable organizational culture founded in a particular period of time may have an imperfectly imitable advantage over firms founded in a different era, where different organizational values and beliefs dominated (Zucker, 1977; Barney, 1986b). Firms are unique and heterogeneous because throughout their history they accumulate different physical assets and different intangible organizational assets of tacit learning and dynamic routines (Peteraf, 1993; Teece *et al.*, 1997).

Causal ambiguity exists when the link between the resources controlled by a firm and a firm's sustained competitive advantage is not well understood or is imperfectly understood (Barney, 1991). To be a source of competitive advantage, firms that possess resources to generate a competitive advantage and those that do not yet possess but are seeking to imitate them must be faced with the same level of causal ambiguity (Lippman and Rumelt, 1982). Ironically, to be a source of competitive advantage, firms must have an imperfect understanding of the link between their resources and sustained competitive advantage. Because resources controlled by a firm are complex and interdependent, hypotheses about these relationships are rarely possible to rigorously test; therefore, the re-

lationship between resources and sustained competitive advantage remains somewhat ambiguous (Barney, 1991).

Barney (1991) stated that resources are imperfectly imitable because they are socially complex and beyond the ability of firms to systematically manage and influence. Examples are interpersonal relations between managers in a firm (Hambrick, 1987), culture (Barney, 1986b), and a firm's reputation among suppliers (Porter, 1980). Competitive advantages based in complex social phenomena constrain the ability of other firms to imitate these resources (Barney, 1991).

Substitutability. Finally, the fourth firm resource attribute required for a resource to potentially generate a sustained competitive advantage is substitutability. Barney (1991) stated there must be no strategically equivalent valuable resources that are themselves either not rare or imitable. Two resources, or bundles of resources, were equivalent if they can be used separately to implement the same strategies (Barney 1991). Figure 1 is Barney's (1991) framework for assessing the potential of firm resources to generate a sustained competitive advantage.

Hoopes *et al.* (2003) agreed with Barney (1991) that causal ambiguity made the copying of a resource or capability imperfectly imitable. They argued though that property rights, which apply most directly to resources, also prevent competitors from copying resources. An example is a patent that prevents another firm from infringing on its product design. Additionally, they reasoned that higher learning and development costs inhibited competitors from trying to copy both resources and capabilities (Hoopes *et al.*, 2003). As the amount of resources needed for investment to copy a rival firm's resource

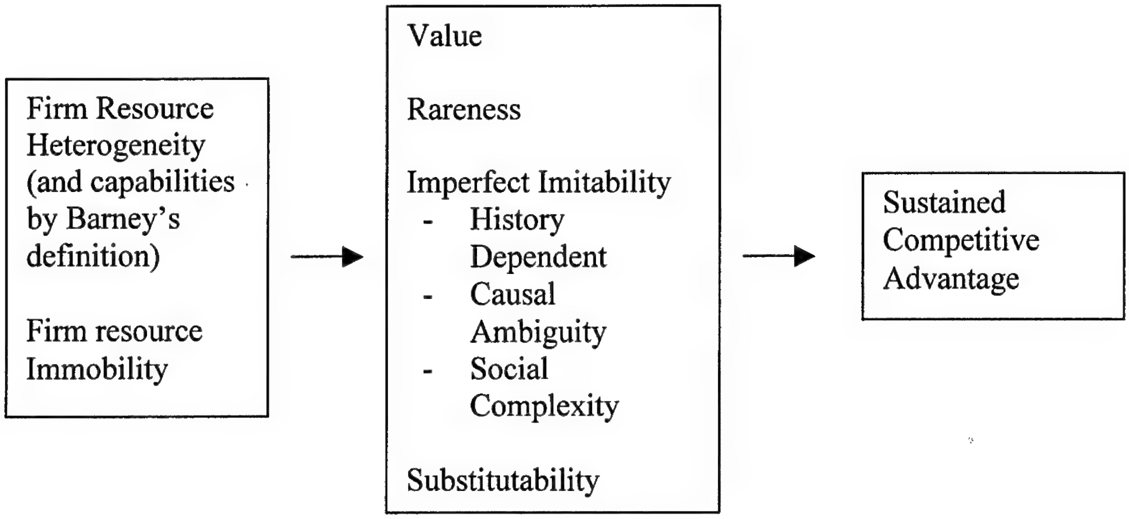

Figure 1. Relationship between resource heterogeneity and immobility; value, rareness, imperfect imitability, and substitutability; and sustained competitive advantage (adapted from Barney, 1991)

or capability increased, the probability that a firm will attempt to imitate the resource or capability decreased (Sutton, 1991).

Bundles of Resources

Although the use of the term "bundles of resources" has been acknowledged in RBV, only a few researchers have addressed the dynamic aspects of bundling resources and their implications to RBV (Black and Boal, 1994). Barnard (1938) recognized that a firm's strategic assets may exhibit complementarity in deployment or application. The strategic value of each asset's relative magnitude may increase with an increase in the relative magnitude of other strategic assets (Amit and Schoemaker, 1993). Dierickx and Cool (1989) called this a positive externality. Teece's (1986) notion of co-specialized assets, those for which there is a bilateral dependence in application, is a similar concept.

Denrell *et al.*'s (2003) concept of commodity resources and complex resources is also similar to the concept of resource bundles. Commodity resources are standardized assets such as years of PhD chemist's time that are typically traded in identifiable markets. Complex resources are then typically created by bringing together commodity resources. These resources are modified or connected in ways that make them more productive than just the sum of their individual productivities.

Mehra (1996) found strong overall associations between firm resource endowments and superior performance. He also found that certain resources conferred a disproportionate degree of advantage, and some of them seemed to work only in particular combinations. Hitt *et al.* (2001) found in professional services firms (law firms) that bundling of complementary resources was associated with positive performance. Senior law partners were paired with junior partners to create work teams in higher performing law firms. Junior partners were used to complete more simple and routine tasks, while at the same time helping more experienced and trained senior partners perform more complex tasks, thereby learning tacit knowledge (Hitt *et al.*, 2001).

RBV and Hospitals

As far as this author can determine, Short *et al.* (2002) provided the only empirical test of RBV in hospitals. In their study of 85 hospitals, they examined the relationship between three types of organizational resources (physical, intangible, and financial) and performance, as measured by return on assets and two efficiency measures: occupancy and admissions per bed. Physical capital was measured by capital investment; intangible assets were measured as direct medical education costs, and financial resources were measured as a hospital's debt to asset ratio. In addition, they tested to see if strategic

group membership affected performance. After controlling for bed size, mixed results were found between resources and performance. Organizational resources were significantly related to return on assets, but not to occupancy or admissions per bed. Group membership was related to occupancy and admissions per bed, but not to return on assets. Finally, group membership moderated the effect of organizational resources on admissions per bed only (Short *et al.*, 2002).

Sustained Competitive Advantage and Performance

Barney (1991: 102) defined sustained competitive advantage as the implementation by a firm of "a value creating strategy not simultaneously being implemented by any current or potential competitor and when these other firms are unable to duplicate the benefits of this strategy." Although some authors defined a firm's competition as only current competitors (Baumol, Panzar, and Willig, 1982), this definition includes potential future competitors (Barney, McWilliams, and Turk, 1989). In contrast to Barney (1991), some authors defined sustained competitive advantage over some period of time (Porter, 1985; Jacobsen, 1988). Lippman and Rumelt (1982) argued that sustained competitive advantage was achieved once efforts by competitors to duplicate that advantage have ceased. This definition of sustained competitive advantage was also an equilibrium definition (Hirshliefer, 1980). This paper relied on Barney's (1991) general definition of sustained competitive advantage that is not time dependent.

Empirical tests have shown that competitive advantage can be gained through tangible and intangible strategic assets. Schroeder *et al.* (2002) showed that competitive advantage in manufacturing (i.e., plant performance as measured by variables such as quality, on time deliveries, cycle time, and flexibility) resulted from proprietary processes

and equipment, which, in turn, was driven by external learning from customers and suppliers and employees' internal learning. Miller and Shamsie (1996) showed that property-based resources helped financial performance of Hollywood film studios in stable environments, whereas knowledge-based resources helped performance in uncertain environments. Collis (1991) showed in the global bearings industry that core competence (production technology and production management skills) and organizational capability (culture) were associated with firm performance. Henderson and Cockburn (1994) showed competency, either in discipline expertise (i.e., Chemistry) or expertise in a particular disease category, was positively associated with performance as measured by research productivity. Pennings *et al.* (1998) found in the Dutch audit industry that human capital strongly predicted firm dissolution and effects depended on their specificity (uniqueness) and nonappropriability (ownership status of that capital). Although the most common measurement of performance of RBV is a firm's financial performance, a number of empirical RBV studies used nonfinancial measures of performance (Tallman, 1991; Henderson and Cockburn, 1994; Judge and Douglas, 1998; Schroeder *et al.*, 2002; Short *et al.*, 2002). Similar to these studies, this research study examined a nonfinancial measure of performance for military hospitals. Appendix A provides a summary of empirical studies using RBV as its theoretical basis.

Hospital Performance Outcomes

Numerous health care providers have adopted multidimensional performance assessment systems in order to better achieve their missions and enhance their competitive positions (Chow, Ganulin, Teknika, Haddad, and Williamson, 1998; Griffith, 1998; Zelman, Blazer, Gower, Bumgarner, and Cancilla, 1999; Griffith and Alexander, 2002).

These multiperformance indicators are often termed the balanced scorecard (BSC), which is a system adopted from leading organizations in the corporate sector (Kaplan and Norton, 1996). According to Voelker, Rakich, and French (2001: 13), the BSC methodology "converts an organization's vision and strategy into a comprehensive set of linked performance and action measures that provide the basis for successful strategic measurement and management." The BSC approach requires that performance indicators selected must have the capability to be compared to competitors and industry standards and must have organizational benchmarks to be able to identify areas for improvement (Simon, 1997). By default, comparable measures must be consistently defined and measured across databases (Griffith and Alexander, 2002). Four major scorecard dimensions are generally accepted as being critical to a firm's long-term success: financial, internal business processes, customer, and learning and growth. Internal business processes include the cost, quality, efficiency, and other characteristics of goods and services a firm provides (Kaplan and Norton, 1996). These dimensions strike a balance between financial and nonfinancial measures and provide a set of forward-looking performance indicators that link strategy to specific actions (Voelker, Rakich, and French, 2001). The BSC approach avoids overemphasis of financial performance measures as hospitals and health care systems respond to ever increasing demands for quality and satisfaction from its consumers (Griffith and Alexander, 2002). This paper examines the relationship between hospital staffing resources and the inpatient quality outcomes as measured by average length of stay (ALOS), in-house mortality rates, and 30-day readmission rates.

Average Length of Stay

ALOS is often used as an indicator of hospital performance (Thomas, Guire, and Horvat, 1997). It is a widely used measure of quality even though it primarily involves resource use (Shojania, Showstack, and Wachter, 2001). It is also commonly viewed as an indictor of hospital efficiency with hospitals having a lower risk-adjusted ALOS viewed as being more efficient. Length of Stay (LOS) has been thought of as a quality indicator in two ways. First, if hospitals discharge patients early in order to save costs under the perspective payment system, then a lower ALOS would be an indicator of poor quality (Hsia and Ahern, 1992). On the other hand, if poor quality of care causes complications, it would increase a patient's LOS (Bradbury, Golec, and Stern, 1994). Based on their analysis of content validity, reliability, and sensitivity of this measure, Griffith and Alexander (2002) concluded that case-mix adjusted LOS was potentially useful in evaluating performance at most U.S. hospitals. They also found that LOS was positively correlated with mortality and negatively associated with cost per case.

Cho, Ketefian, Barkauskas, and Smith (2003) found that the occurrence of an adverse event during hospitalization, such as a patient fall, was associated with a significantly prolonged LOS. Zhan and Miller's (2003) study of 7.45 million discharges from 994 hospitals in 28 states found that medical injuries during hospitalizations added an average of 11 days to a patient's LOS and increased mortality rates by 22% for the most serious event, postoperative sepsis. Thomas *et al.* (1997) found that poor quality care was associated with longer risk-adjusted LOSs. Steel, Gertman, Crescenzi, and Anderson (1981) found a positive relationship between LOS and the presence of complications in general medical patients, whereas the same finding was found for trauma patients (Smith, Martin, Young, and Macioce, 1990).

Although the potential relationship between mortality and LOS has already been discussed, LOS has also been found to be associated with hospital readmission rates. Findings for this relationship will be discussed below. It appears that using LOS is a valid measure of quality.

Mortality Rates

Mortality is widely accepted as a measure of quality outcome (Griffith and Alexander, 2002). The appeal of using mortality rates as a performance measure lies in its unambiguous collection and measurement. Based on their analysis of content validity, reliability and sensitivity of this measure, Griffith and Alexander (2002) concluded that case-mix adjusted mortality rate was potentially useful in evaluating performance at most U.S. hospitals. They did find that mortality and LOS were positively correlated; longer LOSs were associated with higher mortality rates. They also found that hospitals with better case-mix adjusted mortality rates moved more rapidly than others to outpatient care and short LOSs without increases in cost. Dubois, Brook, and Rogers (1987) study of 93 hospitals concluded that adjusted mortality rates were potentially useful to screen hospitals that potentially provide poor quality care.

Others did not believe that case-mix adjusted mortality rates were a good performance indicator. Thomas and Hofer (1999) did not believe that existing mortality adjustment methods were adequate in ensuring interfirm comparisons. As a result, a number of providers have dismissed mortality measures based solely on administrative data (Krumholz, Rathore, Chen, Wang, and Radford, 2002).

It is clear from the discussion above that mortality rates are by no means a perfect indicator for measuring patient quality outcomes. Bond, Raehl, Pitterle, and Franke

(1999: 131) stated "whereas mortality rates are not specific measures of quality of care, they have a close association with it." Due to wide acceptance and use of this measure and evidence of its potential usefulness in detecting poor quality care, case-mix adjusted mortality rates appear to have value as a measure of inpatient quality outcomes.

Mortality rates and LOS have been shown to be positively correlated with each other (Griffith and Alexander, 2002). Roemer, Moustafa, and Hopkins (1968) found that adjusting mortality rates by corrected ALOS explained a large portion of the disparity in the death rates of 33 Los Angeles County hospitals. Goss and Reed (1974) also found similar results in New York City hospitals, though ALOS adjustments explained a much smaller proportion of the variance in mortality rates.

Readmission Rates

Rates of early readmission have been argued to be a measure that represented a combination of both hospital clinical and financial outcomes (Shojania *et al.*, 2001). Hospital readmissions as a measure of quality are based on the assumption that readmissions are preventable (Benbassat and Taragin, 2000). The majority of preventable admissions have been found to occur within 1 month of discharge (Frankl, Breeling, and Goldman, 1991). Numerous researchers have argued that risk-adjusted readmissions rates are useful indicators of quality care that can be compared across hospitals and benchmarked (DesHarnais, Forthman, Homa-Lowry, and Wooster, 2000; Lagoe, Noetscher, and Murphy, 2000;). Francois, Bertrand, Beden, Fauconnier, and Olive (2001) concluded that readmissions were a useful indicator of the quality of care provided in French hospitals. Some studies have also found that readmissions are associated with another potential quality indicator, LOS. Halfon, Eggli, van Melle, Chevalier, Wasserfallen, and Burnand

(2002) found that potentially avoidable readmissions were associated with longer LOS during initial hospitalizations. Tsai, Lee, and Rivers (2001) found that people whose initial hospital LOS was longer than average were more likely to be readmitted within 15 days. Ottenbacher, Smith, Illig, Fiedler, and Granger (2000) also found a similar relationship for patients receiving medical rehabilitation. A meta-analysis of studies published before 1990 also found that longer LOSs was a predictor of readmissions (Camberg, Smith, Beaudet, Daley, Cagen, and Thibault, 1997). This finding, in combination with previous findings showing an association between ALOS and mortality, leads to the conclusion that ALOS potentially represents an indicator of quality care that also affects, but is not a direct cause of, other quality measures.

Others have argued that readmissions are not a good indicator of quality of care. Even though Benbassat and Taragin (2000: 1074) found that 9%-48% of all readmissions were associated with indicators of substandard care during hospitalization, they concluded from their meta-analysis of articles published from 1991-1998 that "global readmission rates are not a useful indicator of quality of care." They believed most readmissions were caused by conditions that could not be controlled by the hospital, such as progression of chronic diseases and patient frailty. Levy, Alsop, Hehir, Lock, Greenwood, and Tobin (2000) found a 10% readmission rate in a 12-month period in their sample of hospitals, but only 5% of the readmissions were preventable.

Even though there is conflicting evidence on the value of readmissions as a measure of inpatient quality of care, readmission rates appear to be a valid measure of quality. Therefore, this study will use 30-day readmission rates as one potential indicator of hospital quality performance outcome.

Registered Nurse, Overall Nurse Staffing, and Outcomes

There have been a number of empirical studies that have examined the relationship between RN staffing and inpatient outcomes with mixed results. Overall, it appears that proper resource allocation of nursing resources may be important for hospitals to improve patient quality outcomes. "Nursing sensitive outcomes" are defined as a "variable patient or family caregiver state, condition, or perception responsive to nursing intervention" (Maas, Johnson, and Moorhead, 1996: 296). Even though this definition applies to a wide range of patient outcomes, the vast majority of studies in this area focus on the occurrence of adverse outcomes (Needleman, Buerhaus, Mattke, Stewart, and Zelevinsky, 2001). Needleman *et al.*'s (2001) review of the literature provided 23 measures of potentially sensitive nursing complications but also identified mortality, LOS, readmission rates, and failure to rescue as potential indicators of nursing care quality.

Aiken, Clarke, Sloane, Sochalski, and Silber (2002) performed a cross-sectional analysis of the relationship between RN staffing and inpatient outcomes in 168 non- federal adult general hospitals in Pennsylvania, utilizing patients in the general, orthopedic, and vascular surgery diagnosis related groups. Staffing was measured as the mean patient load across all staff RNs taken from a survey of nurses at these hospitals, who reported personal patient loads between 1 to 20 patients on their last shifts. Staffing was measured at the hospital level because there is no evidence that specialty-specific staffing offers any advantages in the study of patient outcome and to reflect the fact that patients often receive nursing care in more than one specialty area of a hospital (Needleman *et al.*, 2001). Patient outcomes measured were 30-day mortality and failure-to-rescue rates. Failure-to-rescue was defined as death within 30 days of admission for patients who experienced complications. In addition to using patient risk adjustment factors, three hos-

pital characteristics were used as control variables: bed size, teaching status, and technology. Results showed that each additional patient per nurse lead to a 7% increase in the odds of 30-day mortality and failure-to-rescue.

A federally funded study found the number and mix of hospital nurses impacts patient care quality. Discharge data from 5 million patients in 799 different hospitals across 11 states show that five measures of inpatient outcomes (urinary tract infection, pneumonia, shock, upper gastrointestinal bleeding, and LOS) decreased 3% to 12% during times of high RN staffing. This study had advantages over other studies because it was able to examine the nursing staff structure by separating RNs, aides, and licensed practical/vocational nurses and test the effects of these separate types of resources (Needleman *et al.*, 2001).

Using data from acute care hospitals in California and New York, Lichtig, Knauf, and Milholland (1999) examined the relationship between nursing structure and adverse patient outcomes, including LOS. Nursing intensity weights were used to control for differences in the case-mix of patients. Teaching status (teaching versus nonteaching) and location (rural versus urban) were also used as control variables. The two predictor variables of interest were RN hours and a percentage of total nursing hours and total nursing hours per nursing intensity weight-adjusted patient day. Results showed that more nursing hours per nursing intensity weight and a higher skill mix of nurses are both associated with reduced hospital LOSs (Lichtig *et al.*, 1999).

Bond *et al.* (1999) examined the relationship between staffing levels and mortality in 3763 hospitals across the United States. They found that severity adjusted mortality rates decreased as the level of RNs per occupied bed increased, but mortality rates in-

creased as the level of licensed vocational and practical nurses per occupied bed day (OBD) increased.

Blegen, Goode, and Reed (1998) examined the relationship among total hours of nursing care, nursing skill mix, and adverse patient outcomes, including mortality. The study found that total hours of nursing care was associated with lower mortality, but no relationship between mortality and nursing skill mix was found (Blegen *et al.*, 1998).

Aiken, Smith, and Lake (1994) used Health Care Financing Administration and American Hospital Association data for 39 "magnet" hospitals and five sets of 39 control hospitals to examine the relationship between nurse staffing and outcomes. They found that the higher the overall nurse staffing level and the higher proportion of RNs to overall nursing staff care, the lower the mortality rates.

Hartz, Krakauer, Kuhn, Young, Jacobsen, Gay, Muenz, Katzoff, Bailey, and Rimm (1989) examined 30-day adjusted mortality rates from 3100 hospitals and found that lower mortality rates were related to a higher skill mix in nursing staff among Medicare patients. Financial status, ownership status, teaching status, technological sophistication, and hospital size (beds) were hospital variables that were also analyzed for their effects.

Scott, Forrest, and Brown (1976) also found decreased mortality rates for surgical patients at 17 hospitals when a higher RN ratio (RNs to licensed practical nurses and licensed vocational nurses) in the nursing structure was present.

Three multi-institutional studies did not find a statistically significant association between nurse staffing and patient outcomes. Al-Haider and Wan (1991) and Shortell and Hughes (1988) used Health Care Financing Administration data and found that the proportion of nursing staff that were RNs was unrelated to patient mortality. Shortell, Zim-

merman, Rousseau, Gillies, Wagner, Draper, Knaus, and Duffy (1994) found that the average RN-to-patient ratio in 42 intensive care units (ICUs) was also not related to patient outcomes.

Although not examining the relationship between nurse staffing and outcomes, Cooper, Sirio, Rotondi, Shepardson, and Rosenthal (1999) showed that readmission rates to the ICU can be a complementary measure of hospital performance along with ICU LOS and ICU mortality rates. Readmission rates were not found to be correlated with length of stay or mortality (Cooper et al., 1999).

Physician Staffing and Outcomes

There have been no empirical studies that have been found that directly examined the relationship between time spent by physicians with inpatients and subsequent outcomes in general medical surgical inpatient wards. This was not surprising because, in the majority of hospitals, the physicians who admit and care for inpatients are not employees of the hospital. Therefore, there has been no need to collect the time spent by these physicians while caring for inpatients.

There are two studies that indirectly try to measure the relationship between mortality and physician staffing levels. Bell and Redelmeier (2001) found in a study of a Canadian hospital that the patients admitted on the weekend (a period of less physician and nurse staffing) had a higher mortality rate than for patients admitted on weekdays. Dobkin's (2003) study of California hospitals found that patients admitted on weekends did not have a higher mortality rate than patients admitted on weekdays. Unfortunately, the measure of physician staffing was estimated based on observations made in four "representative" hospitals and extrapolated to the rest of the sample. Dobkin replicated Bell

and Redelmeir's study. After correcting for methodological problems Dobkin believed were in Bell and Redelmier's analysis, no significant relationship was found between weekend admissions and mortality rates.

Due to the lack of studies examining the relationship between hospital physician staffing and patient outcomes, two other streams of research may provide clues as to this relationship: hospitalists and intensivists.

Hospitalists

The hospitalist model of inpatient care is a model where specialized physicians known as hospitalists provide inpatient care to all inpatients in place of primary care physicians (Michota, Lewis, and Cash, 1998). Hospitalist is defined as physicians who devote at least 25% of their time to the care of hospitalized patients (Wachter and Goldman, 1996). Since 1996, this model of inpatient care has experienced significant growth (Wachter and Goldman, 2002). Proponents of the hospitalist model postulate that hospitalists improve inpatient quality care through concentrated care of inpatients and more rapid follow-up of test results due to their on-site availability throughout the day (Grumbach and Fry, 1993; Peabody, Bickel, and Lawson, 1996; Wachter and Goldman, 1996). Wachter and Goldman (2002) found 19 studies that empirically examined the impact of hospitalists on inpatient outcomes. Fifteen studies showed decreases in both costs and LOS, two studies only showed decreases in LOS, and two studies did not show any decreases in costs or LOS. The results for mortality rates and readmission rates were also inconsistent. Most studies did not show any improvements in these outcomes, but two larger and more methodologically rigorous studies did show significant reductions in mortality for patients treated by hospitalists (Wachter and Goldman, 2002).

The shortfall of these studies was that there was no direct measurement of time spent by hospitalists that could be compared to the control groups used to see if the amount of time spent was a factor in patient outcomes. Lurie, Miller, Lindenauer, Wachter, and Cox (1999) found that 85% of hospitalists surveyed reported they cared for between 6 and 20 patients at any given time and assumed the overall average was 13 inpatients per hospitalist. Thus, a hospital with a daily average census of 39 inpatients would need three full-time hospitalists. If we assume that each hospitalist worked 50 hours per week for 50 weeks per year, then we can estimate each patient received 31.6 minutes per day from a hospitalist [(3 hospitalists x 50 weeks x 50 hours per week x 7 days per week x 24 hours per day x 60 minutes per hour) / (39 inpatients per day x 365 days per year)]. If one of the advantages of hospitalists is increased availability, one would expect that, the lower the patient to hospitalist ratio, better outcomes may be expected after controlling for patient and case mix.

Intensivists

The literature on intensivist staffing in ICUs may also provide some insight into the relationship between physician time and inpatient outcome. Intensivists are physicians who specialize in the care of critically ill patients. Staffing ICUs with intensivists may improve clinical outcomes (Vincent, 2000). A conceptual model that may explain this finding is that physicians who have the skills to treat clinically ill patients and who are immediately available to detect and treat problems may prevent or attenuate morbidity and mortality. Intensivists may also decrease resource use because they are potentially better at preventing complications that prolong length of stay (Pronovost, Jenckes, Dorman, Garrett, Breslow, Rosenfeld, Lipsett, and Bass, 1999). Pronovost, Angus, Dorman,

Robinson, Dremsizov, and Young (2002) performed a systematic review of ICU staffing. They classified ICUs as either high intensity (intensivist cares for ICU patients or a mandatory consultation with an intensivist is required for all ICU patients) or low intensity (no intensivist is available or consultation with an intensivist is elective). Although difficult or impossible to determine, the assumption is made that, in high intensity ICUs, more physician time per day is spent with each patient. In their comprehensive review of the literature, Pronovost *et al.* (2002) concluded that high intensity staffing was associated with reduced hospital and ICU mortality and reduced hospital and ICU LOS.

As mentioned before, the one shortfall with these streams of literature was no direct measurement of physician time spent with patients. Although improved patient outcomes may be more a result of care by physicians who are specialized versus more available (and thus time spent caring for patients), this relationship is not clear.

Summary

The literature review above has first shown the lack of articles that examine hospital performance using RBV. The nursing and physician streams of literature give us some ideas of what human resources potentially affect hospital inpatient performance, as defined by ALOS, mortality, and readmission rates. Although it appears that increased RN staffing does improve outcomes, this relationship and its relationship to non-RN staffing is not clear. The physician literature does not contain any studies that directly measure the amount of time spent with inpatients and outcomes, although the literature on hospitalists and intensivists may indicate that more physician time spent with inpatients may lead to better outcomes. RBV appears to be an extremely appropriate and use-

ful theoretical lens through which to examine the relationship between hospital staffing levels and inpatient hospital outcomes.

CHAPTER 3: THEORETICAL AND CONCEPTUAL FRAMEWORK

This study focuses on examining the relationship between resources and patient outcomes. As seen in Chapter 2, there exists a need for further study of this area within the RBV stream of literature in strategic management and within the nursing and physician outcomes literature. This chapter will focus on developing the theoretical framework used in this study and the associated research questions and hypotheses.

Research Model

This study utilizes the RBV as its theoretical basis for its research models. The heart of RBV states that managers in a firm make strategic choices on the accumulation and use of a firm's internal resources, and these choices enable them to generate a sustained competitive advantage (Barney, 1991; Amit and Schoemaker, 1993; Short *et al.*, 2002). The type, magnitude, and nature of a firm's resources and capabilities are integral to its competitive advantage and ultimately its profitability (Amit and Schoemaker, 1993). Figure 2 is a simple view of the RBV.

Only resources and capabilities that have the potential to generate a sustained competitive advantage are strategically relevant and are also known as strategic assets (Barney, 1991). By definition, strategic assets must be somewhat heterogeneous and immobile or else other firms could accumulate and deploy the same assets and compete away any advantage.

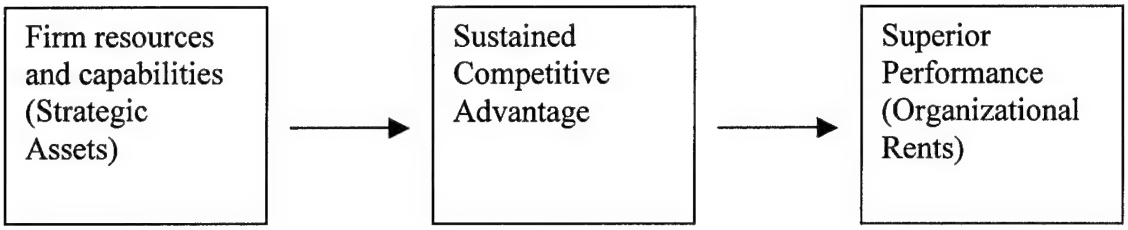

Figure 2. A simple view of the resource-based view/theory

Human assets are a special form of strategic asset (Amit and Schoemaker, 1993). Resource-based theorists have argued that human assets can be a source of sustainable competitive advantage because tacit knowledge and social complexity are hard to imitate (Coff, 1997). Firm-specific human assets refer to special skills, knowledge, or personal relationships that are only applicable to a given firm (Coff, 1997). Resources, including human resources, must be valuable, rare, and imperfectly imitable, with no strategically equivalent substitutes that are themselves either not rare or imitable to potentially be a strategic asset (Barney, 1991).

All hospitals do not provide exactly the same services and thus possess different amounts and types of resources, i.e., strategic assets. In military hospitals, the majority of personnel working within these facilities are military members. There are also a small portion of civilians, both civil service and contracted, mixed in. Military members are somewhat immobile for several reasons. First, military members, unlike civilians, cannot decide just to leave and enter the civilian labor force. Second, even if a readily available supply of nursing personnel and physicians was available, military hospitals are not able to fully replace military medical personnel with civilians. Medical readiness dictates the need to have a sufficient number of militarily trained and deployable medical assets. Fi-

nally, it is not very common for personnel from one Service to work in a hospital in another Service.

Barney (1991) stated a resource is valuable when it enables a firm to conceive of or implement strategies that improve its efficiency or effectiveness. Clearly, RNs, other nursing staff, and physicians are necessary for hospitals to care for inpatients. Whether competing on quality or being the low cost provider, these human resources are needed to provide efficient and effective hospital inpatient services. Therefore, we conclude that RNs, other nursing personnel, and physicians are valuable.

In terms of meeting the criterion of rareness, a resource has the potential of generating a competitive advantage as long as the number of firms possessing the particular valuable resource (or resource bundle) is less than the number of firms needed to generate perfect competitive dynamics in an industry (Hirshliefer, 1980). No studies have argued that any hospital market exhibits perfect competition. Due to mergers and consolidations, many may argue that hospital competition has actually decreased. Therefore, because the number of hospitals (not necessarily beds) in most markets is less than the number needed for perfect competition, these human assets can be considered rare. In addition, the scarcity of a resource may potentially make a resource rare. The shortage of RNs potentially makes these human assets even more rare. A recent study by the Bureau of Health Professions, U.S. Department of Health and Human Services (2002), showed a nationwide shortage of over 100,000 RNs in the year 2000 and projected the (RN) shortage in the United States to be 808,000 by 2020. Even if hospitals wanted to increase the level of RNs, few locations in the country have a readily available supply of nurses (O'Neil and Seago, 2002). From a military standpoint, because military hospitals are the

only hospitals that possess human assets that can provide peacetime inpatient care and are trained for wartime tasks, these assets could be considered as extremely rare.

Human resources have the potential to generate a sustained competitive advantage if they also possess the attribute of being imperfectly imitable (Rumelt, 1982; Barney 1986a, 1986b). As mentioned before, a resource can be imperfectly imitable in one or a combination of three ways: dependent on historical conditions, causally ambiguous, or socially complex (Barney, 1991). Human resources are often causally ambiguous because many social and cognitive processes are not well understood (Coff, 1997). As will be discussed later, some empirical studies have shown a negative relationship between nursing staff levels and patient outcomes, but the specific aspects of the nursing staff causing this relationship have not been clear. Next, tacit knowledge of interpersonal relationships and corporate culture are elements of social complexity (Coff, 1997). Socially complex resources are hard to replicate because they are embedded in complex social systems (Barney, 1991). Because nursing personnel and physicians interact with each other and with numerous other personnel in caring for a patient in a hospital, these human assets have tacit knowledge of their relationships with numerous personnel; they are also part of a socially complex system. In addition, all health care systems, including Air Force, Army, and Navy health care systems, can be said to have unique corporate cultures. Therefore, we can conclude that nursing personnel and physicians are not perfectly imitable because they are causally ambiguous and socially complex.

Finally, the fourth attribute required for a resource to generate a sustained competitive advantage is substitutability. Barney (1991) stated there must be no strategically equivalent valuable resources that are themselves either not rare or imitable. Physicians, RNs, and other nursing personnel are required by law and regulations to receive formal

training and achieve licensure before being allowed to provide care to patients. Only another physician can perform duties for a physician (i.e., writing patient treatment orders). Similarly, certain duties can only be performed by RNs (medication administration), whereas other nursing personnel are permitted to perform less complex duties. Some substitutability in a hierarchical fashion can occur between these three types of personnel. More intensively trained personnel can perform the duties of lesser trained personnel, but not vice versa. Because physicians, nurses, and other nursing personnel are both rare and imitable, we also conclude that there is no substitute for these human assets. As a result, the following proposition is given:

> Proposition 1. Physicians, RNs, and other nursing personnel are considered strategic assets because they are valuable, rare, and imperfectly imitable and have no strategically equivalent substitutes that are themselves either not rare or imitable.

Competitive Advantage Based on Quality Outcomes

Next, strategic assets must be used to generate a sustained competitive advantage for a firm. It appears that many hospitals attempt to generate a sustainable competitive advantage based on quality services (Luft *et al.*, 1986; Woolley and Frech, 1988-1989; Calem and Rizzo, 1995). Therefore, inpatient outcome measurements that represent the level of hospital inpatient quality of services provided would be one indication of the level of competitive advantage achieved by a hospital.

There are numerous ways to measure the quality of inpatient care provided. In this study, ALOS, in-house mortality rate, and 30-day readmission rates will be used to measure quality of care. As mentioned in the previous chapter, these measures have been

widely used as quality measures, though some controversy exists about whether these are valid measures of patient quality.

One assumption implicit in RBV is that the strategic assets of a firm can actually generate the competitive advantage being measured. In addition, it is then assumed that the competitive advantage can directly impact the measure of superior performance, usually measured by profitability. For this paper, it is assumed hospitals that are able to achieve better patient outcomes will also have better financial outcomes (economic rents).

A review of the nursing literature shows that nursing staff, RNs and non-RN staff, does impact the three measures of inpatient quality used in this study (Needleman *et al.*, 2001). Nursing staffs provide daily hands-on care to inpatients in a hospital. The care provided by nurses ranges from monitoring and charting patient vital signs to medication administration. A review of the hospitalists and intensivists literature also shows that physicians directly impact the quality of inpatient care provided. Physicians are responsible for the diagnosis and treatment of patient diseases and illnesses. In general, the findings in these streams of literature show that higher levels of overall nursing staff, RNs, non-RN staff, and physician staffing, lead to better patient outcomes. Higher staffing levels allow for better patient care through increased availability, potentially quicker recognition and treatment of problems, and potential reduction in errors as a result of less workload. Better patient outcomes in this study are defined as shorter ALOS, lower in-house mortality rates, and lower 30-day readmission rates.

Complementary Resources

It also has been shown that the strategic value of each asset's relative magnitude may be affected by the relative magnitude of other strategic assets it is deployed with (Amit and Schoemaker, 1993). The proposed study will also examine if RNs, who are more highly trained and educated, and non-RN support staff, who receive less training and education, are complementary strategic assets. This proposed relationship is similar to the relationship found by Hitt *et al.* (2001) between newly trained lawyers and more experienced lawyers. The effect of the newly trained lawyers on the performance of law firms depended on the level of support/teaching they received from more experienced lawyers and vice versa. In addition, Mehra (1996) found that certain resources were able to generate a disproportionate degree of competitive advantage, but some configuration of these resources was superior to others. These two studies show that combining assets in a particular way can be advantageous to a firm and lead to a competitive advantage.

Other firm resources and factors may also impact inpatient outcome measures. Culture has been identified as a possible strategic asset that may impact the outcomes of a firm (Barney, 1986b; Fiol, 1991). To control for cultural impacts, Service affiliation and teaching status of hospitals were used as control variables in the model. Hospital bed size has also been widely used to control hospital structural characteristics that may also impact hospital performance outcomes; therefore, hospital bed size was included in the model.

Based on the discussion above, the following research questions and hypotheses are presented:

1. Do military health care facilities that provide more total nursing FTEs to care for inpatients experience better patient outcomes?

Hypothesis 1a: Health care facilities that provide more total nursing FTEs per OBD will experience a shorter ALOS.

Hypothesis 1b: Health care facilities that provide more total nursing FTEs per OBD will experience lower in-house mortality rates.

Hypothesis 1c: Health care facilities that provide more total nursing FTEs per OBD will experience lower 30-day readmission rates.

2. Do military health care facilities that provide more RN FTEs to care for inpatients experience better patient outcomes?

   Hypothesis 2a: Health care facilities that provide more RN FTEs per OBD will experience a shorter ALOS.

   Hypothesis 2b: Health care facilities that provide more RN FTEs per OBD will experience lower in-house mortality rates.

   Hypothesis 2c: Health care facilities that provide more RN FTEs per OBD will experience lower 30-day readmission rates.

3. Do military health care facilities that provide more non-RN support staff FTEs to care for inpatients experience better patient outcomes?

   Hypothesis 3a: Health care facilities that provide more non-RN support staff FTEs per OBD will experience a shorter ALOS.

   Hypothesis 3b: Health care facilities that provide more non-RN support staff FTEs per OBD will experience lower in-house mortality rates.

   Hypothesis 3c: Health care facilities that provide more non-RN support staff FTEs per OBD will experience lower 30-day readmission rates.

4. Does the level non-RN support staff moderate the relationship of RN staff levels on inpatient outcomes?

Hypothesis 4a: The level of non-RN support staff will have a positive moderating effect on the impact RN FTEs per OBD has on ALOS.

Hypothesis 4b: The level of non-RN support staff will have a positive moderating effect on the impact RN FTEs per OBD has on in-house mortality rate.

Hypothesis 4c: The level of non-RN support staff will have a positive moderating effect on the impact RN FTEs per OBD has on 30-day readmission rates.

5. Do military health care facilities that provide more physician FTEs to care for inpatients experience better patient outcomes?

Hypothesis 5a: Health care facilities that provide more physician FTEs per OBD will experience a shorter ALOS.

Hypothesis 5b: Health care facilities that provide more physician FTEs per OBD will experience lower in-house mortality rates.

Hypothesis 5c: Health care facilities that provide more physician FTEs per OBD will experience lower 30-day readmission rates.

Figure 3 illustrates the overall theoretical model and relationships as postulated in the hypotheses. No test of the relationship between the competitive advantage, defined by better quality patient care, and superior performance, usually defined by profitability, will be done in this study.

Findings from the hospital outcomes literature show that ALOS is correlated to both mortality rates and readmission rates. Because LOS must always precede an in-house mortality or readmission episode, an alternative theoretical model also based on RBV will be used to test the following research question and associated hypotheses:

6. Does patient LOS directly affect and mediate the impact of staffing resources on patient outcomes?

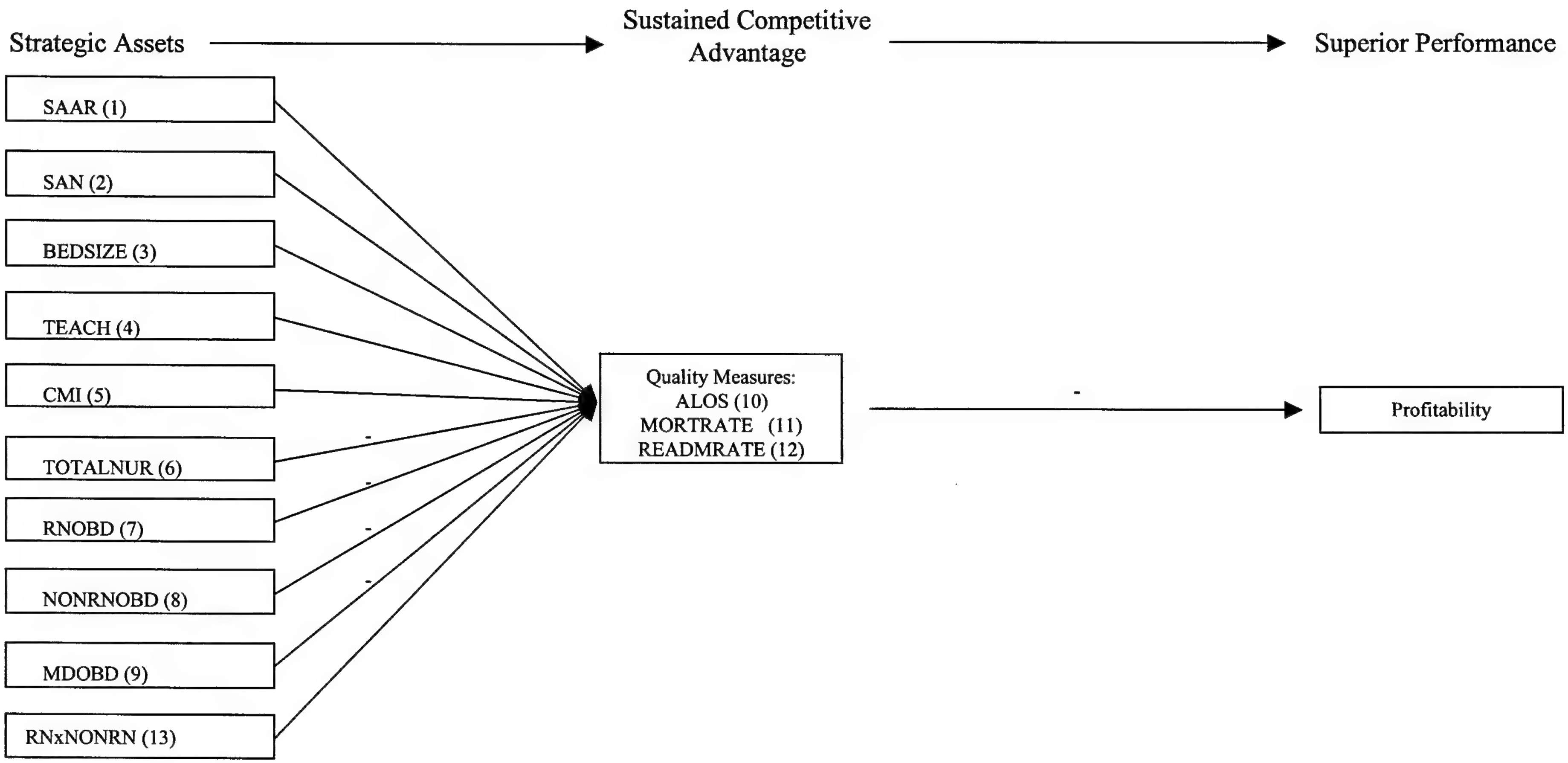

Figure 3. Research Model

Note: SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, RNxNONRN is the interac-tion term representing the moderating effect of the non-RN staff on the RNs, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

Hypothesis 6a: ALOS has a positive relationship with in-house mortality rate and mediates the impact of total nursing staff and physicians on in-house mortality rate.

Hypothesis 6b: ALOS has a positive relationship with in-house mortality rate and mediates the impact of RNs, non-RN staff, and physicians on in-house mortality rate.

Hypothesis 7a: ALOS has a positive relationship with 30-day readmission rates and mediates the impact of total nursing staff and physicians on 30-day readmission rates.

Hypothesis 7b: ALOS has a positive relationship with 30-day readmission rates and mediates the impact of RNs, non-RN staff, and physicians on 30-day readmission rates.

Figure 4 illustrates the alternative theoretical model and relationships as postulated in the hypotheses. Once again, no test of the relationship between the competitive advantage, defined by better quality patient care, and superior performance, defined by profitability, will be done in this study. Appendix B shows the specific models used to test the hypotheses.

Description of Variables

The following section will describe the control, predictor, and dependent variables to be used in this study.

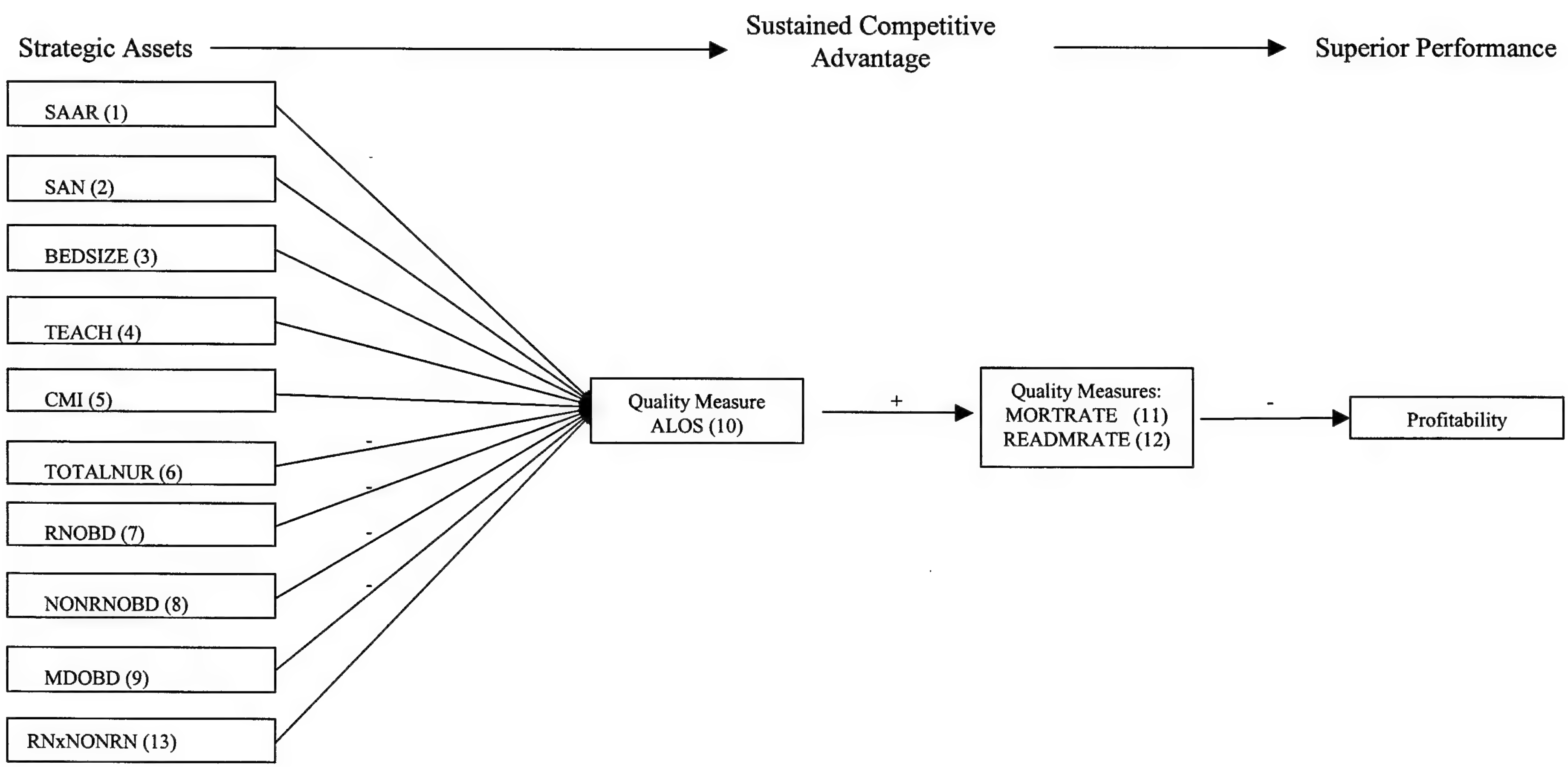

Figure 4. Alternative Research Model

Note: SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, RNxNONRN is the interac-tion term representing the moderating effect of the non-RN staff on the RNs, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

Control Variables

Because this study is attempting to isolate the effects of the levels and types of inpatient staffing on patient outcomes, a number of control variables are needed to eliminate other potential causes affecting patient outcomes.

Service affiliation and teaching status. Medical facility service affiliation is a categorical variable with Air Force medical facilities used as the reference group. Therefore, two dummy coded variables will be used: SAAR will be coded 1 for Army facilities and 0 will be coded for all others; SAN will be coded 1 for Navy facilities and 0 will be coded for all others. Teaching status, TEACH, is a dichotomous variable with 0 representing no graduate medical education training is provided in the facility and 1 representing graduate medical education training is present. As mentioned previously, culture may be a strategic factor that may impact the resources, capabilities, and eventually outcomes of a firm (Barney, 1986b; Fiol, 1991). Service affiliation and teaching status are potentially measures that represent cultural differences.

Facility bed size. To control for possible effects due to hospital structure characteristics, the number of operating beds as listed by each Services' Surgeons General will be used. Bed size is potentially also a proxy to measure efficiency as a result of economies of scale. A review of more than 100 studies by Nuffield Institute for Health, University of Leeds and National Health Service Centre for Reviews and Dissemination, University of York (1996) found that economies of scale are fully exploited in acute care hospitals with 100 to 200 beds, and hospitals with greater than 200 beds displayed diseconomies of scale. By controlling for bed size, any effects of

nursing care and physician care on patient outcomes potentially as a result of economies of scale can be partialed out.

In military hospitals, larger bed size is also associated with the availability of more specialized services available in the facility. This allows larger bedded military hospitals to treat more severely ill patients, thereby having a higher average case-mix index for the facility. Therefore, bed size potentially can represent economies of scale and possibly also account for the case mix treated at the hospital.

Case-mix index. As mentioned earlier, the dependent variables used in this study needed to be adjusted for the severity of cases treated. Differences in the case-mix index have a crucial influence on the interpretation of patient outcome data (Nuffield Institute for Health, University of Leeds and National Health Service Centre for Reviews and Dissemination, University of York, 1996). The purpose of the case-mix adjustment was to control, to the maximum extent possible, the impact of the differences in patient mix. The remaining differences found in outcome measures were hoped to reflect the quality of care provided by hospitals (Silber, Rosenbaum, and Ross, 1995). The case-mix index represented the case complexity of the average inpatient case. Case-mix indexes may be calculated for an entire hospital or for differing levels of analysis (e.g., beneficiary category and clinical area). No severity adjustment system based solely on administrative data is superior for all purposes, and case adjustments made based on diagnosis-related groups appear to be better than other alternatives (Department of Health and Human Services Agency for Healthcare Research and Quality, 2002). There are numerous methods that have been used to adjust for the severity of cases treated at hospitals, such as the Charlson Co-Morbidity Index

(Charlson, Pompei, Ales, and MacKenzie, 1987) and the Deyo adaptation of the Charlson Co-Morbidity Index (Deyo, Cherkin, and Ciol, 1992). The Military Health System currently uses relative weighted products (RWP) to control for differences in the severity of cases treated between military facilities. RWP is a DoD measure of workload credit derived from biometrics dispositions weighted by TRICARE Diagnosis Related Group (DRG) weights. The number of RWPs is a measure of the relative resource consumption of a patient's hospitalization as compared to that of other patients. This is an important distinction, because a more complex case mix from the RWP perspective indicates a higher degree of resource consumption but does not necessarily indicate greater severity of illness or treatment difficulty (Coventry, Gromadzki, Hutchinson, Kiernan, Rogers, Smith, and Spivey, 1995). To remain consistent with current Military Health System practices, RWPs were used as the method to adjust for the severity of cases each hospital treats. Case-mix index in this study was defined as the mean number of RWPs per disposition at each MTF, which represented the average case complexity for the facility.

$$\text{Case-mix index} = \frac{\text{Relative Weighted Products}}{\text{Total \# of Facility Dispositions}} \qquad (1)$$

A complete description of the methodology for calculating case-mix index can be found in *Reference Guide to MHSS Workload Terminology: MHSS Workload Primer* (Coventry *et al.*, 1995).

Predictor Variables

Registered nurse time per occupied bed day. RN time per occupied bed day was a continuous variable using a scale of minutes spent per OBD by an RN. This variable was calculated by first obtaining the total number of available RN FTEs for each month and multiplying this number by 168 (to get hours) and then by 60 to get minutes. An FTE in the military accounting system is equal to 168 hours per month. Available FTEs, in this case, only accounted for the actual time spent on the inpatient units. Any time spent away from the inpatient unit, such as for readiness activities and vacation, was not counted for in available FTEs. Once the total number of RN minutes spent on inpatient care was calculated, this number was then divided by the total number of OBDs.

$$\text{RN time per OBD (minutes)} = \frac{\text{RN Available FTEs x 168 x 60}}{\text{Total Number of OBDs}} \qquad (2)$$

Nonregistered nurse support staff time per occupied bed day. Non-RN support staff time per OBD was a continuous variable using a scale of minutes spent per OBD by support staff such as medical technicians, license practical nurses, and administrative personnel (who provide direct support to the inpatient units). This variable was calculated the same way as RN time per OBD, with the only difference being available FTEs for the non-RN support staff was substituted for available RN FTEs.

$$\text{Non-RN time per OBD (minutes)} = \frac{\text{non-RN Available FTEs x 168 x 60}}{\text{Total Number of OBDs}} \qquad (3)$$

Total nursing staff time per occupied bed day. Total nursing staff time per OBD was a simple additive combination of RN time per OBD and non-RN time per OBD.

Total nursing staff time per OBD (minutes) = RN time per OBD + non-RN time per OBD (4)

Registered nurse/nonregistered nurse support staff time per occupied bed day interaction term. This interaction term tested whether the effect of RN time per OBD is moderated by the level of non-RN support staff time per OBD. Essentially, this tested whether these two strategic assets were complementary. The interaction term representing the moderating effect of the non-RN staff on the RNs will be a continuous variable. This variable was calculated by multiplying RN time per OBD values by non-RN time per OBD values.

RN/nonRN support staff time per OBD interaction term = RN time per OBD x non-RN time per OBD (5)

Physician time per occupied bed day. Physician time per OBD was a continuous variable using a scale of minutes spent per OBD by physicians. This variable was calculated the same way as RN time per OBD, with the only difference being available FTEs for the physicians are substituted for available RN FTEs.

$$\text{Physician time per OBD (minutes)} = \frac{\text{Physician Available FTEs} \times 168 \times 60}{\text{Total Number of OBDs}} \qquad (6)$$

Dependent Variables

Average Length of Stay. Griffith and Alexander's (2002) evaluation of comparative performance measures across hospitals found the LOS was a good measure of performance for hospitals. It has also been shown to be related to in-house mortality and readmissions. ALOS was measured as a continuous variable. It was measured as the mean number of days per dispositions at a facility. As with the other two dependent variables, comparing ALOS across facilities was done once severity of cases treated was adjusted for.

In-house mortality rate. Mortality is widely accepted as a measure of quality outcome (Griffith and Alexander, 2002). Mortality rate was calculated as a ratio of deaths per 100 dispositions. An advantage of this patient outcome measure was that deaths and dispositions were counted in the same manner by all healthcare facilities. The drawback was that raw mortality rates for facilities were deceiving if they were not adjusted for severity of cases treated.

30-Day readmission rate. Thirty-day readmission rates was a ratio of readmissions within 30 days for the same diagnosis per 100 dispositions. In this study, the initial hospitalization always took place in a military hospital, but subsequent readmissions could occur in the same hospital, a different military hospital, or a civilian hospital. This raw outcome measure also suffered the same drawback as raw mortality rates for facilities. It was deceiving if it was not adjusted for severity of cases treated.

CHAPTER 4: RESEARCH METHODOLOGY

This chapter will discuss the methodology used to test the research questions and associated hypotheses developed in the previous chapter. This chapter will first discuss the use of administrative data in this type of research project. Next, a description of the population used and how the data used in this study were gathered is provided. Finally, a description of the two statistical methods used in this study to analyze the data, ordinary least squares regression and path analysis, is given.

Use of Administrative Data

The more patient characteristics that potentially influence a health quality outcome are included in any analysis, the more likely an unbiased assessment of the association between predictor variables such as staffing levels and quality outcome is achieved. Studies that included clinical data to risk adjust outcome measures are most valid (Nuffield Institute for Health, University of Leeds and National Health Service Centre for Reviews and Dissemination, University of York, 1996). The use of administrative data has been criticized for not containing the clinical level data necessary to permit adequate adjustment of underlying patient conditions (Dans, 1993; Jollis, Ancukiewicz, Delong, Pryor, Muhlbaier, and Mark, 1993). Unfortunately, obtaining clinical level data usually entails potentially high cost and effort. This led states such as California and Florida to monitor hospital quality using only administrative data (Greene, 1994; Pine, Norusis, Jones, and Rosenthal, 1997).

Conversely, hospital administrative data are often uniform, relatively inexpensive, available for a large number of patients or populations, and easy to gather. The use of secondary administrative data is an acceptable and encouraged practice among health researchers and is informative about major processes of care (Scinto, Sherwin, Fowler, 2000). As can be seen from the literature review in Chapter 2, many studies solely used administrative data, though some also incorporated clinical data. Hospital administrative data can be used to develop quality indicators of medical care. Although hospital quality of care assessments solely based on administrative data can never be definitive, it can be used to identify potential quality problems (Department of Health and Human Services Agency for Healthcare Research and Quality, 2002). Krakauer, Bailey, Skellan, Stewart, Hartz, Kuhn, and Rimm's (1992) evaluation of the Health Care Financing Administrations (now the Center for Medicare Medicaid Services) mortality measure using only administrative data found that many errors in patient level predictions may offset each other when patient risks and outcomes are aggregated and standardized mortality rates across hospitals are compared. Thomas and Ashcraft (1991) found considerable evidence that risk adjustments based on administrative claims data performed just as well as clinically based risk adjusters in explaining variance in resource outcomes such as LOS. Iezzoni (1997: 666) stated, "administrative data allow for limited insight into the quality and processes of care, errors of omission or commission, and the appropriateness of care." She concluded that administrative data are "probably most useful as screening tools that highlight areas is which quality should be investigated in greater depth" (Iezzoni, 1997: 666).

Study Population and Data

The hypotheses were tested with data from all 75 DoD inpatient health care facilities during the period from October 1, 2001, to September 31, 2002. The data were obtained from secondary administrative databases in the Military Health System. Specifically, personnel full-time equivalent data were obtained from the Expense Assignment System IV (EAS IV). Dispositions and OBDs were extracted from both the Worldwide Reporting system and from EAS IV via the Medical Health System Mart (M2) database. Workload figures for each facility were compared from both databases. When there was more than a 2% discrepancy between these numbers, calls were made to the facility to confirm the proper number. There were six facilities where either dispositions, OBDs, or both where workload figures between the two databases were off by more than 2%. All six facilities unanimously agreed that the figures from M2 were correct. Timing issues related to the transmission of workload figures by facilities to the Worldwide Reporting system database was the cause of the discrepancies in most cases. Therefore, the disposition and OBDs workload figures from M2 were used.

Mortality data were extracted from M2 using two different queries: one query run by this author and the other run by a person employed by the U.S. Air Force Surgeons General's Office who is qualified to run such queries. One query was instructed to count the number of times where the disposition coded was listed as "death," and the other query was instructed to count the number of times a disposition was coded as "80," which also meant death as the disposition. The standard inpatient data records (SIDR) in M2 were used to get this figure. SIDRs are produced for each disposition at every military medical facility. Both queries produced exactly the same number of deaths for each facility.

Readmissions within 30 days was the most difficult to extract from M2. First, the initial disposition must have taken place at a military medical facility between October 1, 2001, and September 30, 2002. Next, the query used unique pseudo social security numbers (unique for each DoD beneficiary admitted) to scan for admissions to either another military medical facility or a civilian hospital. A case was counted as a readmission if it occurred within 30 days of the initial admission with the same Major Diagnostic Group (MDG) code. SIDR records and health care summary records in M2 were searched to find potential readmissions. Health care summary records are similar to SIDRs except health care summary records are generated for every time a DoD beneficiary is discharged from a civilian medical facility. Therefore, this query used 12 months of SIDR records and 13 months of health care summary records to look for readmissions that met the criteria specified.

Data experts at both the TRICARE Management Activity and U.S. Air Force Surgeons General's office agreed the use of readmissions based on MDG was the best available option. Using more specific diagnosis codes such as DRGs may potentially miss readmissions due to different interpretations of DRG codes. Using MDG codes does suffer the risk of counting a readmission that truly is for a different reason than the initial admission at the military medical treatment facility.

The bed size and teaching status information for each hospital was obtained from each Services' Surgeons General's office, intermediate command, or from the facilities themselves. The Army and Navy bed sizes and teaching status information were obtained from their respective Surgeons General's offices. Air Force bed size information was obtained from a mixture of Intermediate Commands or from the facilities directly.

Using fiscal year 2002 data was highly desired due to data quality issues. After speaking with the three Services data quality managers, they unanimously agreed that the workload and personnel time data were much more accurate in 2002 compared to previous years. A list of the 75 inpatient military facilities used is found in Appendix C.

Method of Analysis For Hypotheses 1-5

Ordinary Least Squares Regression

The primary data analysis method used in this study was ordinary least squares regression. Regression analyses are a set of statistical techniques that allow one to assess the relationship between one dependent variable and several independent variables. Each independent variable is assessed in terms of what it added to the explained variation in the dependent variable (Tabachnick and Fidel, 2001). In this study, the control variables, nursing variables, physician variable, and the nursing staff interaction (moderation) term were entered to test for any interaction effects (Hypotheses 4a, 4b, and 4c). An interaction effect is present when the effect of an independent variable on a dependent variable depends on the value of another independent variable. If interaction effects are present, the effects of the nursing variables on each dependent variable must be interpreted with regard to this interaction. In this case, the total effect of a variable is a combination of its separate linear and moderated effect on a dependent variable. Hair, Anderson, Tatham, and Black (1998) stated the overall effect for a predictor variable, X1, whose effect on a dependent variable, Y, is moderated by another predictor variable can be calculated by the following equation:

$$b_{X1total} = b_1 + b_3X_2 \tag{7}$$

where b_1 is the regression coefficient of predictor X_1, and b_3X_2 is the regression coefficient of predictor X_2 times a given level of X_2. If no interaction effects are present, each of the regressions will be rerun without the interaction term, and the main effects of the predictor variables on the dependent variables will be interpreted accordingly.

The sample size, n = 75, exceeds the ratio of more than 7:1 observations to variables as the minimum advocated for regression analysis (Hair et *al.*, 1998), but the small sample size may potentially reduce the power of the significance tests. Power of a hypothesis test is the probability of not committing a type II error. A type II error occurs when the null hypothesis is not rejected when it is in fact false (Bowerman, O'Connell, and Dickey, 1986). Power in this study may be reduced because we do not meet the ratio of 10:1 observations to estimated parameters in each regression equation: three independent variables, one interaction variable, and four control variables require 80 observations (Kline, 1998). This may be resolved by eliminating nonsignificant parameter estimates, especially among control variables, or through the potential elimination of a variable as a result of multicollinearity.

The first step in the process of regression analysis is to perform descriptive, correlation, and multicollinearity studies on the variables in the study. These tests will provide general information about the data, such as missing data or outliers, and determine the strength and direction of association between variables. More importantly, this process will determine if any of the assumptions underlying multiple re-gression analyses were violated. The assumptions underlying multiple regression are as follows: The relationship between the independent and dependent variables is linear, residuals have a mean of zero and are independent, and the variables are normally

distributed and homoscedastic. Results of significance tests of regression coefficients are robust against moderate violations of these assumptions (Kline, 1998). The equations for testing Hypotheses 1a, 1b, and 1c will be as follows:

$$Y' = A + B1\ SAAR + B2\ SAN + B3\ BEDSIZE + B4\ TEACH + B5\ CMI + B6\ TOTALNUR + B9\ MDOBD \quad (8)$$

where Y' represents the dependent variables (mortality rate, ALOS, and readmission rates), A represents the value of Y' when the independent variables are all zero, B1 to B9 represent regression coefficients, SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, and MDOBD is the average amount of time spent by a physician per OBD. The standard F-statistic, which determines the overall significance of the model, the unstandardized and standardized regression coefficients, and their associated t-tests will be examined. The level used for determining significance is $p < .05$.

Testing Hypotheses 2a, 2b, 2c, 3a, 3b, 3c, 4a, 4b, and 4c for this model was performed in two separate phases for each dependent variable. The first phase, testing Hypotheses 4a, 4b, and 4c, included all terms (except total nursing staff time per OBD), including the interaction term. The second phase was performed only if no significant interaction effects were found; the regression was rerun without the interaction term present. In the process of hypotheses testing, variables determined not to be significantly correlated with the performance measure (patient outcome variables) at

the $p < .05$ level were considered nonsignificant, but were kept in subsequent regression analyses for the particular dependent variable being tested.

Increments to ordinary R^2, the standard F-statistic for addition of the interaction term, unstandardized regression coefficients, and standardized regression coefficients and associated significance levels were examined. The F-statistic indicated whether or not the addition of each set of variables in the model was statistically significant (Tabachnick and Fidel, 2001).

For testing these hypotheses, the general regression equations used are as follows:

1. Stage 1 (full model including interaction term):

$$Y' = A + B1\ SAAR + B2\ SAN + B3\ BEDSIZE + B4\ TEACH + B5\ CMI + B7\ RNOBD + B8\ NONRNOBD + B9\ MDOBD + B13\ RNxNONRN \quad (9)$$

where Y' represents the dependent variables (mortality rate, ALOS, and readmission rates), A represents the value of Y' when the independent variables are all zero, B1 to B13 represent regression coefficients, SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, and RNxNONRN is the interaction term representing the moderating effect of the non-RN staff on the RNs.

2. If no interaction effects were found, Stage 2 would rerun the regressions without the interaction term present using the following equation:

$$Y' = A + B1\ SAAR + B2\ SAN + B3\ BEDSIZE + B4\ TEACH + B5\ CMI + B7\ RNOBD + B8\ NONRNOBD + B9\ MDOBD \quad (10)$$

Where Y' represents the dependent variables (mortality rate, ALOS, and readmission rates), A represents the value of Y' when the independent variables are all zero, B1 to B9 represent regression coefficients, SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, and MDOBD is the average amount of time spent by a physician per OBD.

Method of Analysis For Hypotheses 6-7

Path Analysis

To test Hypotheses 6a, 6b, 7a, and 7b, path analysis was used. Path analysis is a method that allows for the decomposing and interpreting of linear relationships among a set of variables (Nie, Hull, and Bent, 1975). This method is based on specifying the relationships between variables in a series of regression-like equations. These relationships are graphically shown in a path diagram with straight arrows depicting causal relationships. Causation requires that three criteria be met. First there must be association between variables. Second, one variable must occur before an-

other. Third, there are no other reasonable causes for the outcome variable. Causation is rarely found, but strong theoretical support can make estimation of causal relationships empirically possible (Hair *et al.*, 1998). Given the association found between ALOS and the two other outcome measures used in this study and the fact that ALOS precedes both mortality and readmission events, path analysis appears appropriate to test these hypotheses. These are fully recursive models where ALOS will be used as a mediating variable between the independent variables and the two remaining outcome variables, mortality rate and readmission rate. Although path analysis attempts to establish causality between variables, ALOS by itself is not proposed to cause mortality and readmissions. Rather, it is proposed that ALOS represents an outcome of some unmeasured quality of care process that is one potential cause of mortality and readmissions. Some possible process causes may potentially be poor care caused by medication errors, failure to diagnose and/or treat problems, etc. For testing Hypotheses 6a, 6b, 7a, and 7b, two regression equations were needed to estimate parameters for each dependent variable, in-house mortality rate and 30-day readmission rate. For Hypotheses 6a and 7a, the following equations were used:

1. Stage 1:

$$\text{ALOS} = \text{A} + \text{B1 SAAR} + \text{B2 SAN} + \text{B3 BEDSIZE} + \text{B4 TEACH} + \text{B5 CMI} + \text{B6 TOTALNUR} + \text{B9 MDOBD} \tag{11}$$

where ALOS represents the dependent variable average length of stay, A represents the value of Y' when the independent variables are all zero, B1 to B9 represent regression coefficients, SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no

graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, and MDOBD is the average amount of time spent by a physician per OBD.

2. Stage 2 of the path analysis will have ALOS as a predictor variable for each of the two separate dependent variables. The regression equation used in this stage was as follows:

$$Y' = A + B1\ SAAR + B2\ SAN + B3\ BEDSIZE + B4\ TEACH + B5\ CMI + B6\ TOTALNUR + B9\ MDOBD + B10\ ALOS \quad (12)$$

where Y' represents the dependent variables (mortality rate and readmission rates), A represents the value of Y' when the independent variables are all zero, B1 to B10 represent regression coefficients, SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, and ALOS is the average length of stay.

In testing Hypotheses 6b and 7b, if interaction effects were found in previous testing, the following ordinary least squares regression equation was used for the first stage for both dependent variables:

1. Stage 1:

$$ALOS = A + B1\ SAAR + B2\ SAN + B3\ BEDSIZE + B4\ TEACH + B5\ CMI + B7\ RNOBD + B8\ NONRNOBD + B9\ MDOBD +$$

B13 RNxNONRN (13)

where ALOS represents the dependent variable average length of stay, A represents the value of Y' when the independent variables are all zero, B1 to B13 represent regression coefficients, SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, MDOBD is the average amount of time spent by a physician per OBD, and RNxNONRN is the interaction term representing the moderating effect of the non-RN staff on the RNs. If no interaction effects were found, the interaction term from the regression equation was dropped.

2. Stage 2 of the path analysis had ALOS as a predictor variable for each of the two separate dependent variables. The regression equation used in this stage was as follows:

Y' = A + B1 SAAR + B2 SAN + B3 BEDSIZE + B4 TEACH +

B5 CMI + B7 RNOBD + B8 NONRNOBD + B9 MDOBD +

B10 ALOS + B13 RNxNONRN (14)

where Y' represents the dependent variables (mortality rate, ALOS, and readmission rates), A represents the value of Y' when the independent variables are all zero, B1 to B13 represent regression coefficients, SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent

by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, and RNxNONRN is the interaction term representing the moderating effect of the non-RN staff on the RNs. Once again, if no interaction effects were found, the interaction term from the regression equation was dropped. Once all the parameters were estimated, these regression coefficients were decomposed to show the direct, indirect, total, and spurious effects of the predictor variables on each of the two final dependent variables, in-house mortality rate and 30-day readmission rate.

CHAPTER 5: RESULTS

This chapter presents the results of the analyses using the data and methods described in the previous section. First, the accuracy and reliability of the data are discussed. Next, sample characteristics for all the variables are shown. Finally, the results of the hypotheses testing of models are given.

Accuracy and Reliability of Data

The personnel FTE data and workload data (dispositions and OBDs) were obtained from EAS IV though two independent data extractions. The author performed one data extraction, and an EAS IV systems expert at Gunter Air Force Base performed the second data extraction. Comparisons for every variable value from each facility were performed. No discrepancies or missing values were found. In addition, assigned FTE values were compared to available FTE values to further ensure available FTE values extracted were within reason.

Workload data (dispositions, OBDs, and RWPs), readmissions, and deaths were extracted from M2. For workload data and deaths, two independent data extractions were performed. One extraction was performed by the author with help from a colleague at the Air Force Surgeons General's Office, and the second data extraction was performed by an data expert under contract to the Air Force Surgeons General's Office. Once again, comparison of data values from both runs showed no differences. Only one data extraction to obtain readmissions was performed because of the com-

plex programming required. Readmission rate data were compared to previously published findings on readmissions in civilian hospitals, such as those reported by the Pennsylvania Health Care Cost Containment Council (2002) and by IPRO (2001) on readmissions of Medicare patients in New York state hospitals. The readmission values found in military hospitals were within the same ranges reported in these previously published reports. Therefore, the readmission data are believed to be accurate and reliable.

Finally, workload data from EAS IV and M2 were reconciled. There were eight facilities that showed small (all less than 5%) discrepancies on one or more workload counts. Calls were placed to the facilities to resolve these workload discrepancies. In every case, the hospitals verified that EAS IV data were accurate and steps would be taken immediately to update M2.

Bed size and graduate medical education teaching facility status were gathered using a variety of methods. For Air Force hospitals, e-mails and personal calls to Intermediate Command Surgeons General's offices and calls to individual facilities were required to obtain completed information. Similar efforts were used to gather Army and Navy information, though fewer calls to individual hospitals were required as a result of more complete information available at their respective Surgeons General's offices.

Data from these separate spreadsheets were imported and combined into a master spreadsheet. Once completed, descriptive statistics were run to ensure the individual variables in the master spreadsheet matched the descriptive statistics for the same variables from the original source spreadsheets. No discrepancies were found. In the end, there were also no missing values in the completed data set.

Sample Characteristics

The original sample consisted of 75 Air Force, Army, and Navy hospitals in operation during fiscal year 2002. This sample consisted of 24 Air Force, 28 Army, and 23 Navy hospitals. Thirty-six percent of the hospitals were classified as graduate medical education teaching facilities with 9 hospitals found in the Air Force, 11 in the Army, and 7 in the Navy. Hospital bed size ranged from 6 to 334 beds. Fifty-nine percent of the hospitals had 50 beds or fewer, whereas another 31% had between 50 to 150 beds. The wide range in the number of beds between the smallest hospital and the largest was also reflected in the workload figures. For example, the smallest hospital in the sample had only 134 dispositions in fiscal year 2002, whereas DoD's largest hospital produced over 19,000 during the same period. These hospitals were distributed throughout the United States and overseas, including the Far East and Europe. Military hospitals ranged from small community hospitals to quaternary level teaching medical centers. The existence of outliers decreased the effective sample size to 69 and 70, depending on which hypothesis was tested. Descriptive statistics are provided in Table 1.

Tests for Outliers, Linearity, Homoscedasticity, Independence of Error Terms, and Normality

The methods used in this analysis, ordinary least squares regression and path analysis, relied on the assumptions of absence of outliers, linearity, homoscedasticity, independence of error terms, and normality. Ordinary least squares regression and path analysis were fairly robust with regard to these assumptions, but serious violations of these assumptions can dramatically affect results and lead to erroneous con-

Table 1. Descriptive statistics for the sample and variables

	N	Min. Value	Max Value	Mean	s.d.
Service Affiliation					
Air Force	24				
Army	23				
Navy	28				
GME Teaching Status					
Air Force	9				
Army	11				
Navy	7				
Independent Variables					
Bed Size	75	6.00	334.00	68.53	70.71
Occupied Bed Days	75	325.00	75,240.00	12,875.03	17,608.26
Dispositions	75	134.00	19,258.00	3,769.36	4,265.94
Relative Weighted Products	75	128.15	19,250.08	3,314.52	4,634.93
Case Mix Index	75	0.38	1.64	0.75	0.25
RNOBD (minutes)	75	240.56	1,281.20	549.20	260.00
NONRNOBD (minutes)	75	251.09	2,288.94	634.39	374.58
MDOBD (minutes)	75	20.19	373.89	108.88	65.41
TOTALNUR (minutes)	75	529.75	3493.22	1183.59	612.75
Dependent Variables					
Average Length of Stay	75	1.87	6.34	2.88	0.871
In-house Mortality Rate	75	0	2.49	0.424	0.565
30-day Readmission Rate	75	3.39	22.34	9.74	3.09

RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, and TOTALNUR is the average amount of time spent by the total nursing staff per OBD.

clusions. As a result, the data were examined graphically, and several tests were performed to identify potentially serious violations of these assumptions.

Outliers were defined as any value greater than three standard deviations from the mean. This resulted in the identification of nine values that were identified as outliers: two cases based on large bed size, two for high mortality rates, one for high readmission rate, one for high ALOS, one for high physician time per OBD, one for high total nursing staff time per OBD, and one for high non-RN time per OBD. The

facility that was an outlier for total nursing staff time per OBD was the same facility that was an outlier for non-RN time per OBD. The cases identified as outliers for bed size, high physician time per OBD, and total nursing staff time per OBD /non-RN time per OBD were not used in any further analyses. The other instances of outliers were only used in the analysis when the outlier variable itself was not involved in a specific hypothesis test. Analysis was performed and led to the conclusion that all outlier values were valid and not a result of erroneous data entry. Reasonable explanations for these values are available. The following discussion regarding the testing for meeting the assumptions of linear regression was done after the removal of the outlier cases when appropriate.

The linearity assumption states that the relationship between the independent and dependent variables is linear. This assumption was examined through the use of partial regression plots. The plots showed that the violations of the linearity assumption were not significant.

Homoscedasticity assumes the variance of residual error should be constant for all values of the independent variables. Scatterplots were used to check for equal variances by plotting the standardized residuals against the standardized predicted values. No significant patterns were found in the plots; therefore, no transformations of the data were needed.

Independence of error terms assumes that predicted values are not related to another prediction or sequencing variable. This is also known as autocorrelation and is more common to see in time series data. Scatterplots of residuals against the possible sequencing variables of service affiliation, bed size, and teaching status appeared

random and did not show any patterns. As a result, no adjustments to the data were made.

Normality is related to homoscedasticity and assumes that residual error terms have a normal distribution. A histogram of standardized residuals showed roughly normal curves. Therefore, no transformations to the data were made.

Cubic transformations were performed in an attempt to reduce the number of outliers. These transformations also aided in improving the linearity and normality assumptions of regression. In the end, these transformations did not significantly change the results of the regression models. The magnitudes of the standardized coefficients did slightly change, but direction and significance of predictors that were used in regressions with transformed variables were identical to regression results using untransformed variables. Due to the difficulty of interpreting the results of regressions using transformed variables, the decision was made to use the untransformed variables and exclude outliers for each regression model.

Correlations and Multicollinearity

Table 2 shows the bivariate correlations for the variables in the analysis using all 75 observations. Appendix D shows the specific correlation matrices and descriptive statistics used for different multiple regression models and path analysis models specific to certain hypotheses. For control variables, results show being an Army hospital was negatively correlated with total nursing staff time per OBD (-.36), RN time per OBD (-.30), and non-RN time per OBD (-.37). This implies that Army hospitals are generally associated with providing less nursing care time per OBD. Bed size was positively correlated with graduate medical education (.60), case-mix index (.58),

Table 2. Bivariate correlations for variables for full sample

	1	2	3	4	5	6	7	8	9	10	11	12
Control Variables												
1. SAAR	1											
2. SAN	-.51**	1										
3. BEDSIZE	.18	.01	1									
4. TEACH	.05	-.08	.60**	1								
5. CMI	.19	-.18	.58**	.48**	1							
Predictor Variables												
6. TOTALNUR	-.36**	.19	-.54**	-.45**	-.25*	1						
7. RNOBD	-.30**	.10	-.60**	-.50**	-.34**	.95**	1					
8. NONRDOBD	-.37**	.25*	-.46**	-.38**	-.17	.98**	.86**	1				
9. MDOBD	-.14	.04	.05	.36**	.10	-.06	-.08	-.05	1			
Dependent Variables												
10. ALOS	.20	-.12	.68**	.44**	.77**	-.48**	-.56**	-.40**	-.06	1		
11. MORTRATE	.08	-.08	.56**	.52**	.74**	-.37**	-.44**	-.30**	.21	.69**	1	
12. READMRATE	-.14	.03	.22	.20	.31**	-.09	-.07	-.10	.18	.20	.22	1

*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$.

SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

ALOS (.44), and in-house mortality rate (.52) but negatively associated with total nursing staff time per OBD (-.54), RN time per OBD (-.60), and non-RN time per OBD (-.46). Case-mix index was positively correlated to all three dependent variables: ALOS (.77), in-house mortality rate (.74), and 30-day readmission rate (.31). This indicates that hospitals that treat sicker patients tend to also have longer ALOSs, higher mortality rates, and higher readmission rates. The strongest relationships found among these variables were between total nursing staff time per OBD, RN time per OBD and non-RN time per OBD with correlations ranging between .86 and .98. This was expected for two reasons. First, total nursing staff time per OBD is a combination of the other two variables. Second, allocation of RN and non-RN nursing staff is based on specific manpower standard ratios. Hospitals still have the ability to adjust actual manning on inpatient wards to meet their specific needs. ALOS was positively correlated to in-house mortality rate (.69) meaning that hospitals with longer ALOSs also tend to have higher mortality rates.

A comparison of the descriptive statistics and correlation matrix containing all 75 observations versus the actual ones used in the analyses was similar with several exceptions. The mean and standard deviation for bed size were smaller due to the removal of the two largest military hospitals based on bed size. The correlation betweenbed size and Army hospitals and the positive correlation between Navy hospitals and total nursing staff time per OBD were significant. Finally, 30-day readmission rate was significantly correlated to bed size, graduate medical education, ALOS, and in-house mortality rate.

Multicollinearity was also checked. As expected, significant multicollinearity existed between total nursing staff time per OBD and RN time per OBD and between

total nursing staff time per OBD and non-RN time per OBD. Without total nursing staff time per OBD, tolerances for remaining independent variables ranged from .18 to .81. RN time per OBD and non-RN time per OBD had the lowest tolerances at .18 and .20, respectively. This means we need to acknowledge that these two variables are highly correlated but are not below the common cutoff threshold value of .10 (Hair et *al.*, 1998). Therefore, all independent variables were retained for analysis, but total nursing staff time per OBD was never used with either RN time per OBD or non-RN time per OBD in the same model.

Interaction Effects on Patient Outcomes

Because interpretation of unstandardized regression coefficients of main effects cannot be made properly when the possibility of interaction is present, hypotheses that proposed the presence of interaction effects were tested first. Table 3 shows results of the ordinary least squares regression analysis to test for the presence of interaction (moderating) effects in predicting patient outcomes.

Hypothesis 4a, which proposed an interaction effect between the level of RN staffing and non-RN staffing on the patient outcome variable ALOS, was not supported. There were also no significant relationships between this same interaction term and the patient outcome variables of in-house mortality and 30-day readmission rate. Therefore, Hypotheses 4b and 4c were also not supported. Because no interaction effects were present in any of the three ordinary least squares regression equations, the interaction term was removed, and ordinary least squares regressions were rerun to test for the main effects of predictor variables on the dependent variables.

Table 3. Summary table of regression results for hypotheses 4a, 4b, and 4c

	Dependent Variables					
	ALOS		MORTRATE		READMRATE	
Df	(9, 60)		(9, 59)		(9, 60)	
	b	β	b	β	b	β
(Constant)	2.42 ***		-.40		5.07	
SAAR	-.21	-.13	-.06	-.06	-.70	-.13
SAN	-.08	-.05	-.09	-.09	.67	.12
BEDSIZE	.00	.25*	.00	.14	.01	.15
TEACH	-.16	-.10	.17	.17	.01	.00
CMI	1.82 ***	0.55 ***	1.07 ***	.53 ***	4.23 *	0.39 *
RNOBD	.00	-0.48 *	.00	-.27	.00	.24
NONRNOBD	.00	-.19	.00	.10	.00	-.35
MDOBD	.00	-.13	.00	.06	.01	.17
RNxNONRN	.00	.38	.00	.10	.00	.21
R^2	.70		.65		.25	
Adj. R^2	.65		.59		.14	
F	15.41 ***		11.97 ***		2.25 *	

*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$

SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, RNxNONRN is the interaction term representing the moderating effect of the non-RN staff on the RNs, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

Main Effects on Patient Outcomes

Table 4 shows the results for Hypotheses 1a, 1b, and 1c. Hypothesis 1a proposed that total nursing personnel staffing has a direct negative effect on ALOS. The model testing Hypothesis 1a was significant overall (F = 19.16, $p < .001$) and accounted for 68% of the variation seen in ALOS. Total nursing staff time per OBD had a significant negative relationship with ALOS in the model. This is in the direction

Table 4. Summary table of regression results for hypotheses 1a, 1b, and 1c

	Dependent Variables					
	ALOS		MORTRATE		READMRATE	
Df	(7, 62)		(7, 61)		(8, 61)	
	b	β	b	β	b	β
(Constant)	1.88***		-.51**		4.77*	
SAAR	-.20	-.13	-.08	-.08	-.43	-.08
SAN	-.04	-.03	-.06	-.06	.35	.06
BEDSIZE	.01**	.32**	.00	.17	.01	.16
TEACH	-.14	-.09	.18	.18	-.08	-.01
CMI	1.88***	.57***	1.11***	.55***	3.94**	.37**
TOTALNUR	-.00*	-.23*	-.00	-.05	.00	.12
MDOBD	-.00	-.14	.00	.05	.01	.18
R^2	.68		.64		.24	
Adj. R^2	.65		.60		.15	
F	19.16***		15.33***		2.75*	

*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$

SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

hypothesized. A 100-unit increase in total nursing staff time per OBD lead to a .06 decrease on average in ALOS, controlling for all other independent variables. Case-mix index and bed size also were significant variables in this model and had the two largest relative impacts on ALOS. Hypothesis 1a was supported.

Hypotheses 1b proposed that total nursing personnel staffing has a direct negative effect on in-house mortality rate. The overall model was significant (F = 15.33, p < .001) and accounted for 64% of the variation seen in in-house mortality rate. Total nursing staff time per OBD effect was not significant, but the direction of the effect

was consistent with the hypothesis. Case-mix index was the only variable significant in the model. Hypothesis 1b was not supported.

Hypotheses 1c proposed that total nursing personnel staffing has a direct negative effect on 30-day readmission rate. The overall model was significant ($F = 2.75, p < .05$) and accounted for 24% of the variation seen in 30-day readmission rate. Total nursing staff time per OBD effect was not significant, and the direction of the effect was against what was hypothesized. Case-mix index was the only variable significant in the model. Hypothesis 1c was not supported.

Table 5 shows the results for Hypotheses 2a, 2b, 2c, 3a, 3b, 3c, 5a, 5b, and 5c. Hypothesis 2a, 3a, and 5a proposed direct effects of RN staffing, non-RN staffing, and physician staffing on the patient outcome variable ALOS. Although the overall model was statistically significant ($F = 17.25, p < .001$) and accounted for 69% of the variation seen in ALOS, none of the predictor variables were significant at the $p < .05$ significance level. RN time per OBD t-test value of $p = .057$ was just above the $p < .05$ significance level. The model which tested for interaction effects did show that the coefficient for RN time per OBD was significant ($p = .043$) in predicting ALOS. The coefficients for RN time per OBD in both models were in the proper direction and similar in magnitude. A one-unit increase in RN time per OBD resulted in a -.001 unit decrease on average in ALOS, controlling for all other variables. The standardized regression coefficients showed that RN time per OBD had the second largest relative impact on ALOS, behind case-mix index, in both models.

The control variables bed size and case-mix index were also significant variables in the model, with case-mix index accounting for the largest portion of explained variation seen in ALOS. A one-unit increase in case-mix index lead to a 1.82 unit

Table 5. Summary table of regression results for hypotheses 2a, 2b, 2c, 3a, 3b, 3c, 5a, 5b, and 5c

	Dependent Variables					
	ALOS		MORTRATE		READMRATE	
Df	(8, 61)		(8, 60)		(8, 61)	
	b	β	b	β	b	β
(Constant)	2.00***		-0.47*		4.28*	
SAAR	-.16	-.10	-.05	-.06	-.61	-.11
SAN	-.11	-.06	-.09	-.10	.62	.11
BEDSIZE	.00**	.30**	.00	.15	.01	.18
TEACH	-.16	-.10	.17	.17	.00	.00
CMI	1.82***	.55***	1.07***	.53***	4.21**	.39**
RNOBD	.00	-.33	.00	-.23	.00	.32
NONRNOBD	.00	.09	.00	.17	.00	-.20
MDOBD	.00	-.13	.00	.06	.01	.17
R^2	.69		.65		.25	
Adj. R^2	.65		.60		.15	
F	17.25***		13.67***		2.55*	

*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$

SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

increase on average in ALOS, controlling for all other independent variables. The direction of the coefficients for RN time per OBD and physician time per OBD were in the direction as hypothesized, but the direction of the coefficient for non-RN time per OBD was opposite of what was hypothesized. Overall, Hypothesis 2a received partial support, but Hypotheses 3a and 5a were not supported.

Hypothesis 2b, 3b, and 5b proposed direct effects of RN staffing, non-RN staffing, and physician staffing, respectively, on the patient outcome variable in-house

mortality rate. Although the overall model was statistically significant ($F = 13.67$, $p < .001$) and accounted for 65% of the variation seen in in-house mortality rate, none of the predictor variables were significant at the $p < .05$ significance level. Only the control variable case-mix index was significant in the model. The standardized coefficients showed that case-mix index had the largest impact on in-house mortality rate, followed by RN time per OBD. The direction of the coefficient for RN time per OBD was in the direction as hypothesized, but the directions of the coefficients for non-RN time per OBD and physician time per OBD were opposite of what was hypothesized. Therefore, because the variables representing the level of RN staffing, the level of non-RN staff, and the level of physician staffing were not statistically significant, Hypotheses 2b, 3b, and 5b were not supported.

Hypothesis 2c, 3c, and 5c proposed direct effects of RN staffing, non-RN staffing, and physician staffing, respectively, on the patient outcome variable 30-day readmission rate. Although the overall model was statistically significant ($F = 2.55$, $p < .05$) and accounted for 25% of the variation seen in 30-day readmission rates, none of the predictor variables were significant at the $p < .05$ significance level. Only the control variable case-mix index was significant in the model. Similar to the findings with in-house mortality rate, the standardized coefficients showed that case-mix index had the largest impact on 30-day readmission rate, followed by RN time per OBD. The direction of the coefficient for non-RN time per OBD was in the direction as hypothesized, but the directions of the coefficients for RN time per OBD and physician time per OBD were opposite of what were hypothesized. Overall, because the variables representing the level of RN staffing, the level of non-RN staff, and the level of

physician staffing were not statistically significant, Hypotheses 2c, 3c, and 5c were also not supported.

Path Analysis Results

Table 6 shows a summary of the path analysis regressions for Hypothesis 6a, and Figure 5 is the accompanying path diagram. For simplicity sake, only path coefficients for the predictor variables and significant control variables are shown in all path diagrams. Table 7 shows a summary of the direct, indirect, and total effects of predictor variables on the dependent variable in-house mortality rate. Hypothesis 6a proposed that ALOS has a positive relationship with in-house mortality rate and also mediates the effect of the predictor variable, total nursing staff time per OBD, on the dependent variable in-house mortality rate. Overall, the model was significant ($F = 13.34$, $p < .001$) and explained 64% of the variation seen in in-house mortality rate. Among the control variables, case-mix index and graduate medical education were statistically significant. Among the remaining independent variables, only the mediating variable, ALOS, was significant. ALOS had a positive direct effect on in- house mortality rate. A one-unit increase in ALOS lead to a .21 unit increase in in-house mortality rate on average, controlling for all other independent variables. Case-mix index and graduate medical education both had a positive direct effect on in-house mortality rate. Being a graduate medical education teaching facility lead to a.21 unit increase in in-house mortality rate on average, controlling for all other variables. RN time per OBD had a negative direct effect on in-house mortality rate as hypothe- sized. Non-RN time per OBD and physician time per OBD had a positive direct effect on in-house mortality rate, which is opposite of what was hypothesized.

Table 6. Summary table of path analysis results for hypothesis 6a

Df	(8, 59)
	β
SAAR	-.04
SAN	-.05
BEDSIZE	.06
TEACH	.22 *
CMI	.34 **
TOTALNUR	.04
MDOBD	.10
ALOS	.33 *
R^2	.64
Adj. R^2	.60
F	13.34 ***

*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$

SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, and ALOS is the average length of stay.

Table 7 shows the direct, indirect, total, and spurious effects for Hypothesis 6a. ALOS had the largest direct and total effect (P_{1110} = .35) on in-house mortality rate. Approximately 49% (.33/.68) of the causal effect of ALOS on in-house mortality rate was spurious. Case-mix index had the largest indirect effect (.19) and the largest total effect (.53) on in-house mortality rate. Approximately 25% (.18/.71) of the causal effect of case-mix index on in-house mortality rate was spurious. Among the other predictor variables of interest, total nursing staff time per OBD had a positive direct effect (P_{116} = .04) and a negative indirect effect (-.08), through ALOS, on in-house mortality rate. The total effect of total nursing staff time per OBD on in-house mortality

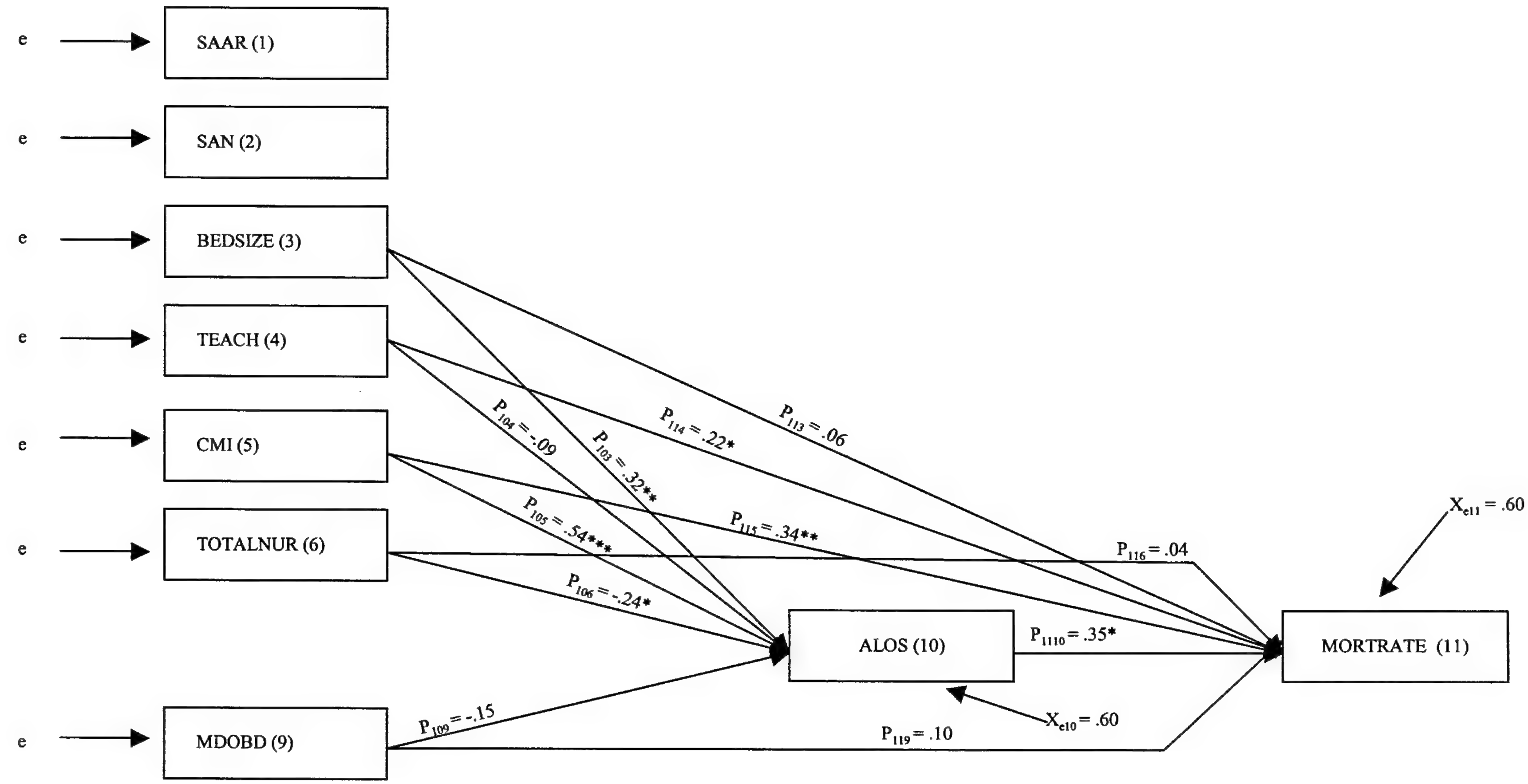

Figure 5. Path analysis diagram for hypotheses 6a

Note: * Significant at the 0.05 Level (2-tailed) ** Significant at the 0.01 Level (2-tailed) *** Significant at the 0.001 Level (2-tailed). For simplicity sake, the curved (double-arrowed) lines representing the correlations between the independent variables in addition to arrows from control variables to ALOS and MORTRATE have been omitted and only path coefficients for predictor and significant control variables are shown. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, and MORTRATE is the in-house mortality rate.

Table 7. Summary table of direct, indirect, and total effects for hypothesis 6a

	Bivariate	b	Path	D.E. (β)	I.E. via	I.E.	Total Effect	Non-Causal
r_{110}	.16	-.20	P_{101}	-.13	--	--	-.13	.29
r_{210}	-.09	-.04	P_{102}	-.02	--	--	-.02	-.06
r_{310}	.61	.00	P_{103}	.32	--	--	.32	.29
r_{410}	.35	-.15	P_{104}	-.09	--	--	-.09	.44
r_{510}	.70	1.92	P_{105}	.54	--	--	.54	.15
r_{610}	-.49	.00	P_{106}	-.24	--	--	-.24	-.26
r_{910}	-.03	.00	P_{109}	-.15	--	--	-.15	.13
r_{111}	.09	-.03	P_{111}	-.04	X_{10}	-.05	-.08	.17
r_{211}	-.10	-.05	P_{112}	-.05	X_{10}	-.01	-.06	-.04
r_{311}	.54	.00	P_{113}	.06	X_{10}	.11	.17	.37
r_{411}	.55	.21	P_{114}	.22	X_{10}	-.03	.19	.36
r_{511}	.71	.73	P_{115}	.34	X_{10}	.19	.53	.18
r_{611}	-.37	.00	P_{116}	.04	X_{10}	-.08	-.05	-.32
r_{911}	.24	.00	P_{119}	.10	X_{10}	-.05	.05	.19
r_{1011}	.68	.21	P_{1110}	.35	--	--	.35	.33

rate was negative (-.05). Overall, Hypothesis 6a was supported because ALOS was significant in predicting in-house mortality rate, while showing that total nursing staff time per OBD had a moderately sized mediated (indirect) effect on in-house mortality rate.

Table 8 shows a summary of the path analysis regressions for Hypothesis 6b, and Figure 6 is the accompanying path diagram. Table 9 shows a summary of the direct, indirect, and total effects of predictor variables on the dependent variable in-house mortality rate. Hypothesis 6b proposed that ALOS has a positive relationship with in-house mortality rate and also mediates the effect of the predictor variables on the dependent variable in-house mortality rate. Overall, the model was significant ($F = 11.83$, $p < .001$) and explained 65% of the variation seen in in-house mortality rate. The mediating variable, ALOS, was significant in this model. ALOS had a positive

Table 8. Summary table of path analysis results for hypothesis 6b

Df	(8, 59)
	β
SAAR	-.04
SAN	-.05
BEDSIZE	.06
TEACH	.22*
CMI	.34**
TOTALNUR	.04
MDOBD	.10
ALOS	.33*
R^2	.64
Adj. R^2	.60
F	13.34***

*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$

SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, and ALOS is the average length of stay.

direct effect on in-house mortality rate. A one-unit increase in ALOS lead to a .20 unit increase in in-house mortality rate on average, controlling for all other independent variables. RN time per OBD, non-RN time per OBD, and physician time per OBD were not statistically significant. RN time per OBD had a negative direct effect on in-house mortality rate as hypothesized. Non-RN time per OBD and physician time per OBD had a positive direct effect on in-house mortality rate, which is opposite of what was hypothesized. Among the control variables, only case-mix index was statistically significant. Case-mix index had a positive direct effect on in-house mortality rate.

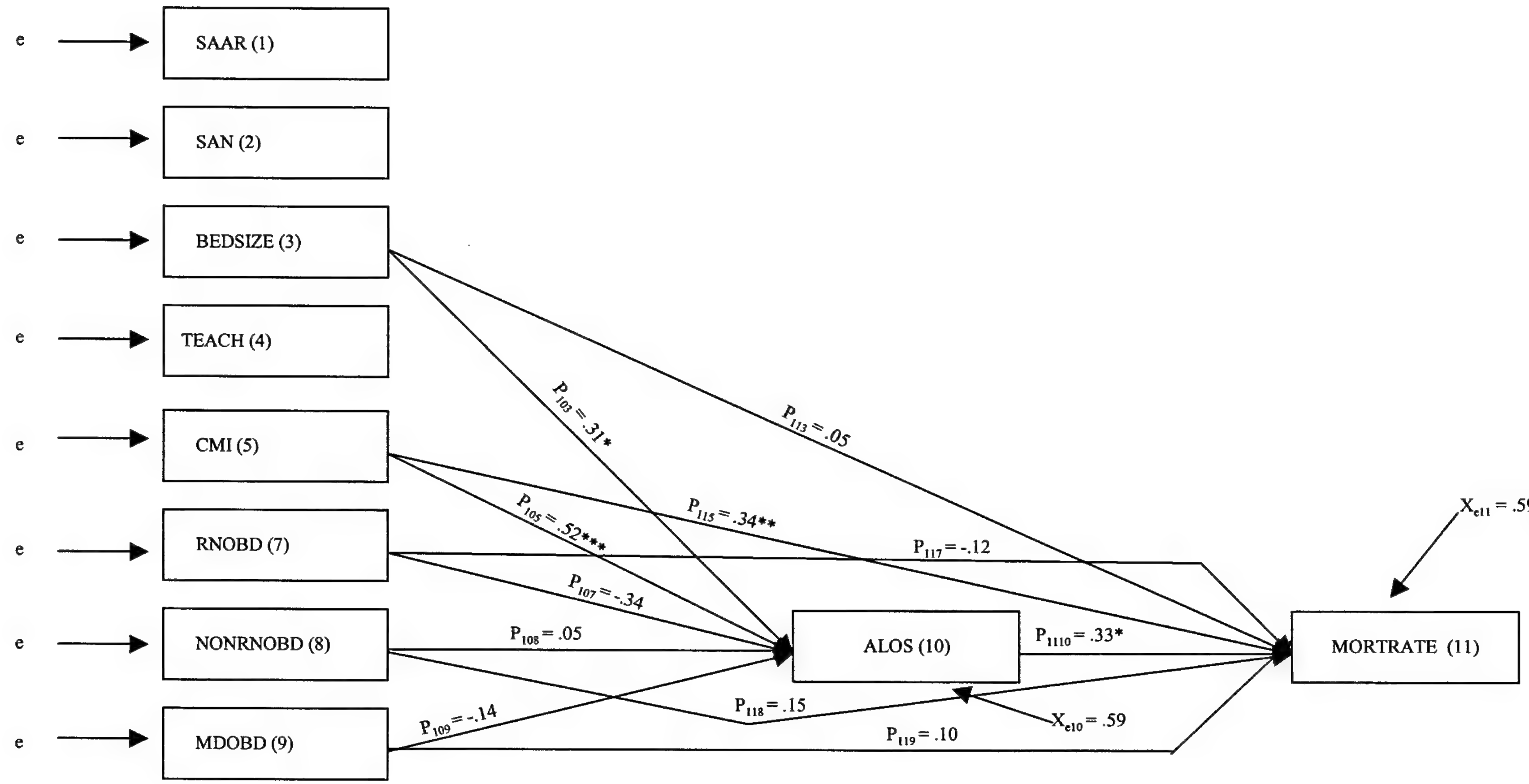

Figure 6. Path analysis diagram for hypotheses 6b

Note: * Significant at the 0.05 Level (2-tailed) ** Significant at the 0.01 Level (2-tailed) *** Significant at the 0.001 Level (2-tailed). For simplicity sake, the curved (double-arrowed) lines representing the correlations between the independent variables in addition to arrows from control variables to ALOS and MORTRATE have been omitted and only path coefficients for predictor and significant control variables are shown. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, and MORTRATE is the in-house mortality rate.

Table 9 shows the direct, indirect, total, and spurious effects for Hypothesis 6b. Case-mix index had the largest direct effect, $P_{105} = .34$, the largest indirect effect (.17), and the largest total effect (.51) on in-house mortality rate. Approximately 28% (.20/.71) of the causal effect of case-mix index on in-house mortality rate was spurious. ALOS had the second largest direct effect and total effect ($P_{109} = .33$) on in-house mortality rate. Approximately 51% (.35/.68) of the causal effect of ALOS on in-house mortality rate was spurious. Among the other predictor variables of interest, RN time per OBD had both a negative direct effect ($P_{106} = -.12$) and a negative indirect effect (-.11), through ALOS, on in-house mortality rate. RN time per OBD had the third largest total effect (-.23) on in-house mortality rate behind case-mix index and ALOS.

Table 9. Summary table of direct, indirect, and total effects for hypothesis 6b

	Bivariate	b	Path	D.E. (β)	I.E. via	I.E.	Total Effect	Non-Causal
r_{110}	.16	-.16	P_{101}	-.10	--	--	-.10	.27
r_{210}	-.09	-.10	P_{102}	-.07	--	--	-.07	-.02
r_{310}	.61	.00	P_{103}	.31	--	--	.31	.30
r_{410}	.35	-.16	P_{104}	-.11	--	--	-.11	.45
r_{510}	.70	1.86	P_{105}	.52	--	--	.52	.17
r_{710}	-.55	.00	P_{107}	-.34	--	--	-.34	-.21
r_{810}	-.42	.00	P_{108}	.09	--	--	.09	-.51
r_{910}	-.03	.00	P_{109}	-.14	--	--	-.14	.12
r_{111}	.09	-.02	P_{111}	-.02	X_{10}	-.03	-.06	.15
r_{211}	-.10	-.07	P_{112}	-.08	X_{10}	-.02	-.10	.00
r_{311}	.54	.00	P_{113}	.05	X_{10}	.10	.16	.38
r_{411}	.55	.20	P_{114}	.21	X_{10}	-.03	.18	.37
r_{511}	.71	.72	P_{115}	.34	X_{10}	.17	.51	.20
r_{711}	-.43	.00	P_{117}	-.12	X_{10}	-.11	-.23	-.19
r_{811}	-.30	.00	P_{118}	.15	X_{10}	.03	.18	-.48
r_{911}	.24	.00	P_{119}	.10	X_{10}	-.05	.05	.19
r_{1011}	.68	.20	P_{1110}	.33	--	--	.33	.35

Non-RN time per OBD had a positive direct effect (P_{107} = .15) and a positive indirect effect (.03), through ALOS, on in-house mortality rate. Physician time per OBD had a positive direct effect (P_{108} = .10) on in-house mortality rate but a negative indirect effect (-.05) through ALOS. The total effect of physician time per OBD on in-house mortality rate was positive (.05). Overall, Hypothesis 6b was partially supported because ALOS was significant in predicting in-house mortality rate, and RN time per OBD had a moderately sized mediated (indirect) effect on in-house mortality rate.

Table 10 shows a summary of the path analysis regressions for Hypothesis 7a, and Figure 7 is the accompanying path diagram. Table 11 shows a summary of the direct, indirect, and total effects of predictor variables on the dependent variable 30-day readmission rate. Hypothesis 7a proposed that ALOS has a positive relationship with 30-day readmission rate and also mediates the effect of the predictor variable, total nursing staff time per OBD, on the dependent variable 30-day readmission rate. Overall, the model was significant (F = 2.23, $p < .05$) and explained 23% of the variation seen in 30-day readmission rate. The only variable to have a significant direct effect on 30-day readmission rate in this model was case-mix index. ALOS had a negative effect on 30-day readmission rate, which is opposite of what was hypothesized. Total nursing staff time per OBD and physician time per OBD had a positive direct effect on 30-day readmission rate.

Table 11 shows the direct, indirect, total, and spurious effects for Hypothesis 7a. Case-mix index had the largest direct effect (.41), largest indirect effect (-.06), and the largest total effect (.35) on 30-day readmission rate. ALOS had the largest direct and total effect (P_{109} = .35) on 30-day readmission rate. Approximately 10% (.04/.39)

Table 10. Summary table of path analysis results for hypothesis 7a

Df	(8, 60)
	β
SAAR	-.09
SAN	.05
BEDSIZE	.19
TEACH	-.03
CMI	.41 *
TOTALNUR	.10
MDOBD	.16
ALOS	-.12
R^2	.23
Adj. R^2	.13
F	2.23 *

*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$

SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, and ALOS is the average length of stay.

of the causal effect of CMI on 30-day readmission rate was spurious. Among the other predictor variables of interest, total nursing staff time per OBD had a positive direct effect (.10) and a positive indirect effect (.03), through ALOS, on 30-day readmission rate. The total effect of total nursing staff time per OBD on 30-day readmission rate was positive (.12). Overall, Hypothesis 7a was not supported because ALOS was not significant in predicting 30-day readmission rate, and total nursing staff time per OBD's indirect effect on 30-day readmission rate was small.

Table 12 shows a summary of the path analysis regressions for Hypothesis 7b, and Figure 8 is the accompanying path diagram. Table 13 shows a summary of the di-

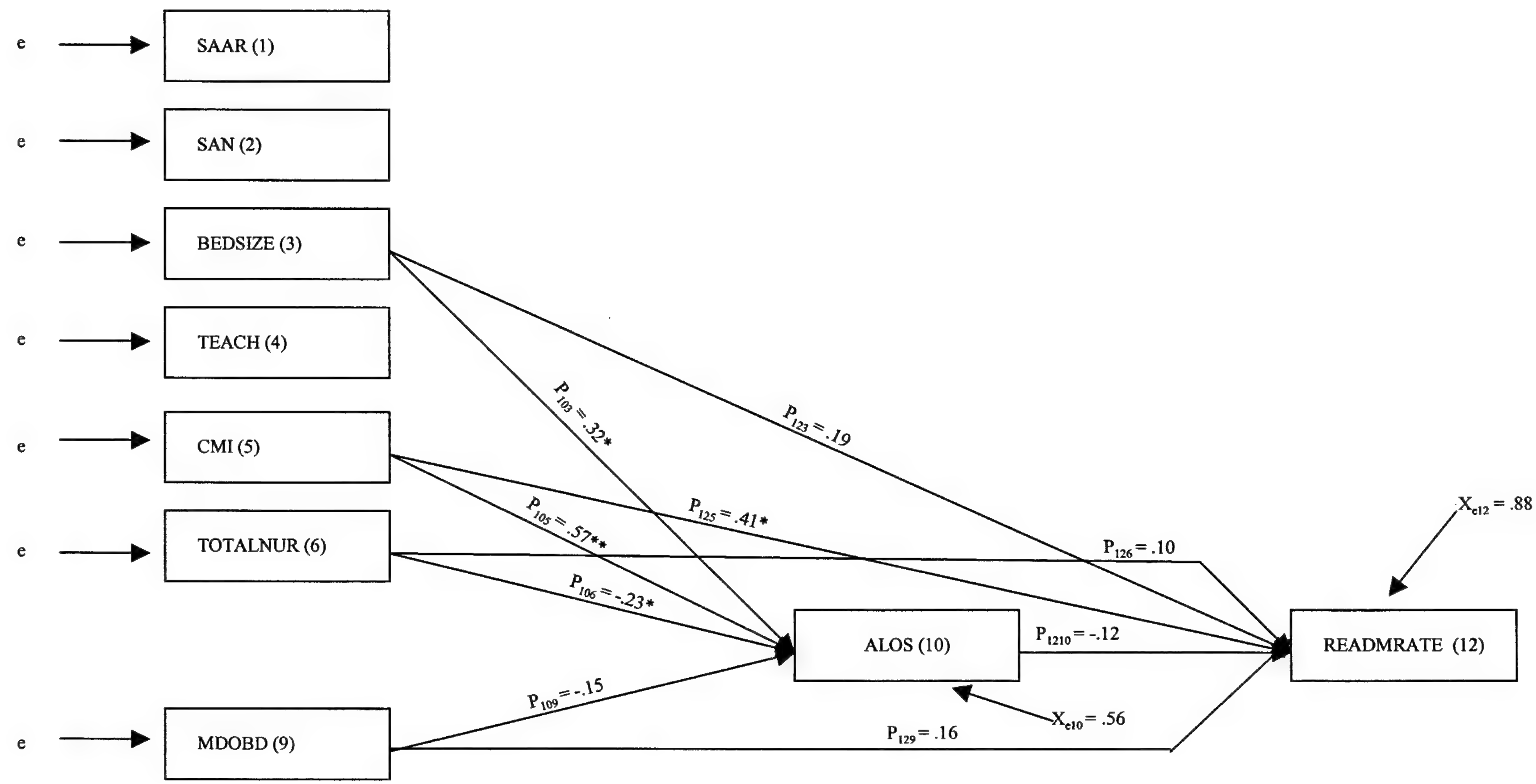

Figure 7. Path analysis diagram for hypotheses 7a

Note: * Significant at the 0.05 Level (2-tailed) ** Significant at the 0.01 Level (2-tailed) *** Significant at the 0.001 Level (2-tailed). For simplicity sake, the curved (double-arrowed) lines representing the correlations between the independent variables in addition to arrows from control variables to ALOS and MORTRATE have been omitted and only path coefficients for predictor and significant control variables are shown. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, and READMRATE is the 30-day readmission rate.

Table 11. Summary table of direct, indirect, and total effects for hypothesis 7a

	Bivariate	b	Path	D.E. (β)	I.E. via	I.E.	Total Effect	Non-Causal
r_{110}	.20	-.18	P_{101}	-.12	--	--	-.12	.31
r_{210}	-.12	-.13	P_{102}	-.08	--	--	-.08	-.04
r_{310}	.65	.00	P_{103}	.32	--	--	.32	.34
r_{410}	.37	-.17	P_{104}	-.10	--	--	-.10	.48
r_{510}	.74	1.82	P_{105}	.55	--	--	.55	.19
r_{610}	-.50	.00	P_{106}	-.23	--	--	-.23	-.27
r_{910}	-.03	.00	P_{109}	-.15	--	--	-.15	.12
r_{112}	-.08	-.52	P_{121}	-.09	X_{10}	.01	-.08	.00
r_{212}	.10	.32	P_{122}	.05	X_{10}	.01	.06	.04
r_{312}	.27	.01	P_{123}	.19	X_{10}	-.04	.16	.11
r_{412}	.23	-.15	P_{124}	-.03	X_{10}	.01	-.01	.24
r_{512}	.39	4.77	P_{125}	.41	X_{10}	-.06	.35	.04
r_{612}	-.02	.00	P_{126}	.10	X_{10}	.03	.12	-.15
r_{912}	.26	.01	P_{129}	.16	X_{10}	.02	.18	.08
r_{1012}	.22	-.41	P_{1210}	-.12	--	--	-.12	.34

rect, indirect, and total effects of predictor variables on the dependent variable 30-day readmission rate. Hypothesis 7b proposed that ALOS has a positive relationship with 30-day readmission rate and also mediates the effect of the predictor variables on the dependent variable 30-day readmission rate. Overall, the model was significant (F = 2.55, $p < .05$) and explained 24% of the variation seen in 30-day readmission rate. Only the control variable, case-mix index, was statistically significant. No other control, predictor, or mediating variables were significant. Case-mix index had a positive direct effect on 30-day readmission rate.

RN time per OBD and physician time per OBD had a positive direct effect on 30-day readmission rate, which is opposite of what was hypothesized. Non-RN time per OBD had a negative direct effect on 30-day readmission rate, just as hypothesized.

Table 12. Summary table of path analysis results for hypothesis 7b

Df	(9, 59)
	β
SAAR	-.12
SAN	.10
BEDSIZE	.20
TEACH	-.01
CMI	.42 *
RNOBD	.30
NONRNOBD	-.19
MDOBD	.15
ALOS	-.08
R^2	.24
Adj. R^2	.13
F	2.55 *

*** $p \le 0.001$; ** $p \le 0.01$; * $p \le 0.05$

SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, and ALOS is the average length of stay.

Table 13 shows that direct, indirect, total, and spurious effects for Hypothesis 7b. Case-mix index had the largest direct effect, $P_{115} = .42$, the largest indirect effect (-.05), and the largest total effect (.37) on 30-day readmission rate. Approximately 5% (.02/.39) of the causal effect of case-mix index on 30-day readmission rate was spurious. RN time per OBD had the second largest direct effect ($P_{116} = .30$), indirect effect (.03) and total effect (.33) on 30-day readmission rate. Among the other predictor variables of interest, non-RN time per OBD had both a negative direct effect ($P_{117} = -.19$) and a negative indirect effect (-.01), through ALOS, on 30-day readmission rate. Non-RN time per OBD had the third largest total effect (-.20) on 30-day readmission

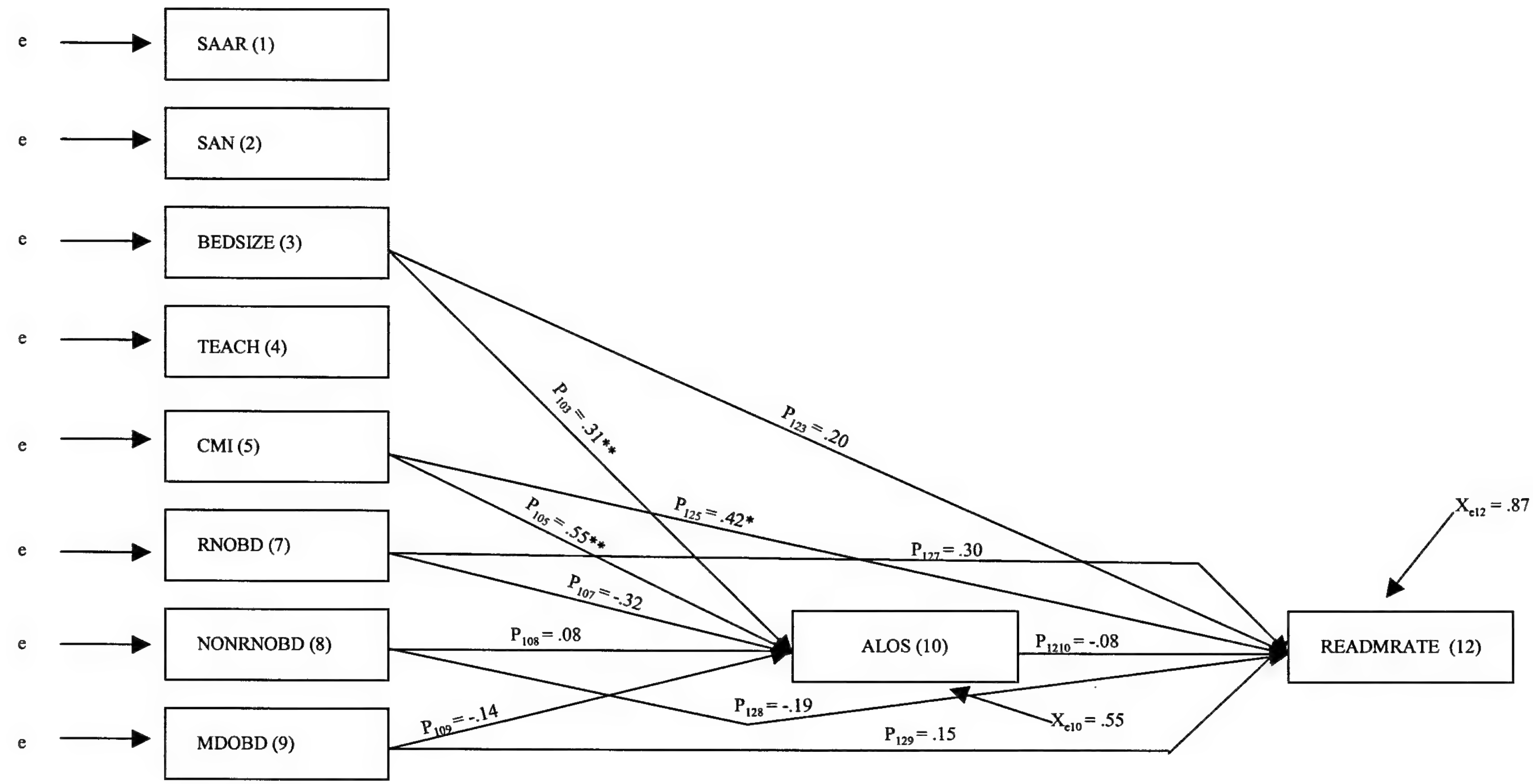

Figure 8. Path analysis diagram for hypotheses 7b

Note: * Significant at the 0.05 Level (2-tailed) ** Significant at the 0.01 Level (2-tailed) *** Significant at the 0.001 Level (2-tailed). For simplicity sake, the curved (double-arrowed) lines representing the correlations between the independent variables in addition to arrows from control variables to ALOS and MORTRATE have been omitted and only path coefficients for predictor and significant control variables are shown. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, and READMRATE is the 30-day readmission rate.

Table 13. Summary table of direct, indirect, and total effects for hypothesis 7b

	Bivariate	b	Path	D.E. (β)	I.E. via	I.E.	Total Effect	Non-Causal
r_{112}	-.08	-.67	P_{121}	-.12	X_{10}	.01	-.11	.03
r_{212}	.10	.57	P_{122}	.10	X_{10}	.01	.11	-.01
r_{312}	.27	.01	P_{123}	.20	X_{10}	-.03	.18	.09
r_{412}	.23	-.06	P_{124}	-.01	X_{10}	.01	.00	.23
r_{512}	.39	4.81	P_{125}	.42	X_{10}	-.05	.37	.02
r_{712}	-.04	.00	P_{127}	.30	X_{10}	.03	.33	-.37
r_{812}	-.01	.00	P_{128}	-.19	X_{10}	-.01	-.20	.19
r_{912}	.26	.01	P_{129}	.15	X_{10}	.01	.16	.09
R_{1012}	.22	-.29	P_{1210}	-.08	--	--	-.08	.31

rate behind case-mix index and RN time per OBD. Physician time per OBD had both a positive direct effect ($P_{118} = .15$) and indirect effect (.01) on 30-day readmission rate. The relationship between ALOS and 30-day readmission rate was not significant, and the negative effect of ALOS on 30-day readmission rate (-.08) was opposite to what was hypothesized. Overall, because ALOS did not have a significant relationship with 30-day readmission rate and the mediated (indirect) effects of the predictor variables were very small, Hypothesis 7b was not supported.

Comparison of Models Explaining In-House Mortality Rates and 30-Day Readmission Rates

Table 14 shows a comparison of models that attempt to predict in-house mortality rate and 30-day readmission rate. Model 1 in each case only proposed a direct effect from total nursing staff time per OBD to the dependent variables. Model 2 in each case proposed direct effects from RN time per OBD, non-RN time per OBD, and physician time per OBD to the dependent variables. One version of Model 2 included

Table 14. Model comparisons

	Model Effects	Adj. R^2	Change in R^2
Dependent Variable: ALOS			
Model 1	Direct	.65	
Model 2	Direct w/o interaction term	.65	.00
Model 2	Direct w/ interaction term	.65	.00
Dependent Variable: MORTRATE			
Model 1	Direct	.60	
Model 2	Direct w/o interaction term	.59	-.01
Model 2	Direct w/ interaction term	.60	.00
Model 3	Direct and Mediated (TOTALNUR)	.60	.00
Model 4	Direct and Mediated	.59	-.01
Dependent Variable: READMRATE			
Model 1	Direct	.15	
Model 2	Direct w/ interaction term	.14	-.01
Model 2	Direct w/o interaction term	.15	.00
Model 5	Direct and Mediated (TOTALNUR)	.13	-.02
Model 6	Direct and Mediated	.13	-.02

TOTALNUR is the average amount of time spent by the total nursing staff per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

the interaction term representing the moderating effect of the non-RN staff on the RNs.

For models predicting ALOS, all of the models had adjusted R^2 values of .65. They all accounted for about 65% of the variation seen in ALOS. The addition of an interaction term in Model 2 did not significantly increase the explanatory power of the model. Therefore, Model 2 without the interaction term was the best model to use because it shows in more detail, compared to Model 1, which specific hospital staffing resource is significant in impacting ALOS. It was most likely the best specified model of the three tested.

For models predicting in-house mortality rate, all of the models were essentially the same in explanatory power. They all accounted for about 60% for the variation seen in in-house mortality rate. Model 4 was most likely the best specified model, even though it was more complex than Models 1 and 2. It shows in more detail the way specific types of hospital staffing resources impact in-house mortality rate, both directly and indirectly through ALOS.

The models attempting to account for variations in 30-day readmission rate were the weakest in explanatory power relative to the models explaining variations in ALOS and in-house mortality rate. The best model could only explain 15% of the variation seen in 30-day readmission rate. In no model were any of the predictor variables or the mediating variable significant. Therefore, because Model 1 was the least complex and had the highest adjusted R^2 value, it would appear to be the best model of the five tested in this study.

Summary of Results

In summary, only 2 of the 12 hypotheses that proposed direct effects on the three separate dependent variables of ALOS, in-house mortality rate, and 30-day readmission rate were supported. Two of the four hypotheses that proposed ALOS as a mediating variable between the predictor variables and the two separate variables, in-house mortality rate and 30-day readmission rate, received partial support. None of the three hypotheses that proposed a moderating effect of non-RN support staff on the effects of RN staffing on outcomes were supported.

Hypothesis 1a proposed that total nursing staff time per OBD has a negative direct effect with ALOS. Support was found for this hypothesis. Hypothesis 2a

proposed that RN time per OBD has a negative direct effect on ALOS. The model that included the interaction term found that RN time per OBD was significant in predicting ALOS. When the interaction term was removed, the coefficient for RN time per OBD was no longer significant ($p = .057$). Therefore, Hypothesis 2a received partial support. No support was found for Hypotheses 1b, 1c, 2b, 2c, 3a, 3b, 3c, 5a, 5b, and 5c. Because no support for interaction between RNs and non-RN staff was found, Hypotheses 4a, 4b, and 4c were also not supported.

Hypothesis 6a proposed that ALOS has a positive relationship with in-house mortality rate, and the effect of total nursing staff time per OBD on in-house mortality rate was mediated by ALOS. Support was found for these two relationships. No support was found for an indirect effect of physician time per OBD on in-house mortality rate. Therefore, Hypothesis 6a was partially supported. Hypothesis 6b also received partial support because ALOS was a significant predictor of in-house mortality rate, and one moderately sized mediated effect of a predictor variable (RN time per OBD) on in-house mortality rate was also found. No support was found for Hypotheses 7a and 7b. A summary is provided in Table 15.

Table 15. Summary of results

Hypotheses

H_{1a}: Health care facilities that provide more total nursing FTEs per OBD will experience a shorter ALOS. **Supported.**

H_{1b}: Health care facilities that provide more total nursing FTEs per OBD will experience lower overall mortality rates. **Not Supported.**

H_{1c}: Health care facilities that provide more total nursing FTEs per OBD will experience lower 30-day readmission rates. **Not Supported.**

H_{2a}: Health care facilities that provide more RN FTEs per OBD will experience a shorter ALOS. **Partially Supported.**

H_{2b}: Health care facilities that provide more RN FTEs per occupied bed day (OBD) will experience lower overall mortality rates. **Not Supported.**

H_{2c}: Health care facilities that provide more RN FTEs per OBD will experience lower 30-day readmission rates. **Not Supported.**

H_{3a}: Health care facilities that provide more non-RN support staff FTEs per OBD will experience a shorter ALOS. **Not Supported.**

H_{3b}: Health care facilities that provide more non-registered nurse support staff FTEs per OBD will experience lower overall mortality rates. **Not Supported.**

H_{3c}: Health care facilities that provide more non-RN support staff FTEs per OBD will experience lower 30-day readmission rates. **Not Supported.**

H_{4a}: The level of non-RN support staff will have a positive moderating effect on the impact RN FTEs per OBD has on ALOS. **Not Supported.**

Table 15 (Continued)

H_{4b}: The level of non-RN support staff will have a positive moderating effect on the impact RN FTEs per OBD has on overall mortality rate. **Not Supported.**

H_{4c}: The level of non-RN support staff will have a positive moderating effect on the impact RN FTEs per OBD has on 30-day readmission rates. **Not Supported.**

H_{5a}: Health care facilities that provide more physician FTEs per OBD will experience a shorter ALOS. **Not Supported.**

H_{5b}: Health care facilities that provide more physician FTEs per OBD will experience lower overall mortality rates. **Not Supported.**

H_{5c}: Health care facilities that provide more physician FTEs per OBD will experience lower 30-day readmission rates. **Not Supported.**

H_{6a}: ALOS has a positive relationship with mortality rate and mediates the impact total nurse staffing and physicians on mortality rate. **Partially Supported.**

H_{6b}: ALOS has a positive relationship with mortality rate and mediates the impact of RNs, non-RN staff, and physicians on mortality rate. **Partially Supported.**

H_{7a}: ALOS has a positive relationship with 30-day readmission rates and mediates the impact of total nurse staffing and physicians on 30-day readmission rates. **Not Supported.**

H_{7b}: ALOS has a positive relationship with 30-day readmission rates and mediates the impact of RNs, non-RN staff, and physicians on 30-day readmission rates. **Not Supported**

ALOS is average length of stay, FTE is full-time equivalent, OBD is occupied bed day, and RN is registered nurse.

CHAPTER 6: DISCUSSION AND IMPLICATIONS, FURTHER RESEARCH, OTHER FINDINGS, LIMITATIONS, AND CONCLUSIONS

Discussion and Implications

The purpose of this study was to evaluate whether military hospitals were able to achieve a competitive advantage, as defined by better quality patient outcomes, through the strategic allocation of inpatient manpower resources. RBV was used as a theoretical framework in this study. The current study, approved by the Institutional Review Board at The University of Alabama at Birmingham (Appendix E), evaluated the relationships and effects that RNs, non-RN support staff, physicians, and other characteristics related to military hospitals have on the inpatient quality outcomes as measured by ALOS, in-house mortality rates, and 30-day readmission rates. Even though previously published findings in the nursing and physician literature tend to show that higher staffing levels generally lead to better patient outcomes of lower ALOS, lower in-house mortality rates, and lower readmission rates, this study provides support only for some of these assertions.

First, an explanation of findings will be discussed based on the resource type (total nursing staff, RNs, non-RN staff, and physicians). A section discussing minor findings will follow. Finally, sections for limitations of this study, suggestions for future research directions, and final conclusions of the study will follow.

Impact of Total Nursing Staff

Results from the study found support for the hypothesized direct relationship between total nursing staff time per OBD and ALOS. As the amount of total nursing time spent on inpatient care increased, ALOS decreased. Starting with mean values for the hospitals used the in sample, a 10% increase in total nurse staffing would reduce ALOS by 1.3% on average. This result supports previously published findings in this area (Aiken et *al.*, 1994; Blegen *et al.*, 1998; Lichtig *et al.*, 1999). No significant direct effects were found between total nursing staff time per OBD and in-house mortality rate, but the path analysis showed that total nursing staff time per OBD's negative effect on in-house mortality rate is accounted for through its indirect effect through ALOS. It appears that the negative impact of total nursing staff time per OBD on ALOS also indirectly lowers in-house mortality rate. Because ALOS is thought to represent an indirect measure of other quality care processes such as nosocomial infection rates and medication error rates, efforts by the entire nursing staff in improving these quality care processes appear to reduce both ALOS and in-house mortality rate.

No significant relationships were found between total nursing staff time per OBD and 30-day readmission rate. There are several possible explanations for this. First, the relatively small sample size may make the detection of significant effects more difficult. Second, the decision to use Major MDGs as the criteria to determine if admission was really a true readmission can also have an impact. Using MDGs may have counted readmissions that were for a different clinical reason from the original admission. This may have potentially inflated readmission figures and caused them to be invalid. Next, there may truly not be a significant relationship between total nur-

sing staff time per OBD and 30-day readmission rate. Other variables not included in the model, such as the level of discharge planning and case management, may be more appropriate for inclusion into the model.

Another possibility for the lack of significant relationships between staffing levels and 30-day readmission rate and the relatively low explanatory power of the models is that 30-day readmission rate may not be a useful quality of care measure. Benbassat and Taragin (2000) and Levy *et al.* (2000) argued that most readmissions were not preventable and were outside the control of the hospital. They believed variables such as progression of chronic disease and patient frailty were the main causes of readmissions. Care provided while in the hospital cannot effectively impact these conditions and is a reason why readmission rates may not be a good measure of quality patient care.

Finally, providing high quality care while in the hospital does not guarantee that, when the patients leave the hospital, they also receive adequate discharge planning, case management services, or care at home. Failure to provide patients with the proper information and follow-up care instructions after being discharged may lead to premature readmissions to the hospital. Case management services are not usually provided by nurses on the inpatient wards. These reasons can be used to explain the lack of significant findings between the different types of medical personnel resources used in this study and 30-day readmission rate.

Impact of RN Staffing

Previously published studies have generally found a significant relationship between the level of RN staffing and patient outcome. Studies have found that an

increase in RN staffing leads to lower LOSs (Lichtig *et al.*, 1999; Needleman *et al.*, 2001) lower mortality rates (Bond *et al.*, 1999; Aiken *et al.*, 2002), and potentially lower readmission rates (Needleman *et al.*, 2001). Even though the overall models were all significant in explaining the variance seen in patient outcomes, this study only found two significant relationships between RN staffing and these patient outcomes. In the model (with no interaction term present) testing for the direct effect of RNs on ALOS, the coefficient for RN time per OBD was almost significant (p = .057). The same model with an interaction term included showed RN time per OBD to be significant (p = .043). Depending on the model used and starting with mean values for the hospitals in the sample, a 10% increase in the amount of RN time spent per OBD lead to a 2.98% to 4.15% reduction in ALOS. Case-mix index and bed size were also statistically significant in explaining the variation seen in ALOS, in-house mortality rate, and 30-day readmission rate. The direct impact of RN staffing on patient outcomes is mixed. Although support for RN staffing impact on ALOS was found as hypothesized, no support was found for RN staffing on in-house mortality rates or 30-day readmission rates. These last two findings are similar to previous studies performed by Al-Haider and Wan (1991), Shortell *et al.* (1994), and Shortell and Hughes (1988).

The results of the path analysis show that RN staffing has a moderately sized indirect effect (-.11) on in-house mortality rate through ALOS. As with total nursing staff time per OBD, RN efforts that reduce ALOS also appear to indirectly reduce in-house mortality rate. This indirect effect was in the direction hypothesized and of similar magnitude to the nonsignificant direct effect. Path analysis also showed that RN

staffing did not have a significant direct effect or indirect effect on 30-day readmission rate.

Overall, these results show that increases in RN staffing appear to have a significant direct effect on reducing ALOS, an indirect effect (through ALOS) of reducing in-house mortality rate, and no effect on 30-day readmission rate. These findings imply that increasing RN staff appears to allow RNs to provide better care to patients that improves the quality of patient outcomes by reducing patient LOS and also indirectly lowers the chance of death while in the hospital.

Even though the entire population of hospitals is included in the original sample, the ability to continue to add nurses to reduce ALOS and in-house mortality rate will most likely not remain a linear function after a certain level. The relationship between nurse staffing and the outcome variables ALOS and in-house mortality rate may be more accurately represented by a diminishing marginal utility returns curve. As more nursing personnel are added above a certain level, their relative ability to improve patient outcomes increasingly diminishes. The sample size and limited range of staffing level values make this level impossible to calculate. The nonsignificant effect of RN staffing on 30-day readmission rate also may be explained by the reasons mentioned in the previous section.

Impact of Non-RN Staffing

Several studies have found that higher overall nurse staffing (RNs and non-RNs) is associated with better patient outcomes such as lower ALOS and lower mortality rates (Aiken *et al.* 1994; Blegen *et al.*, 1998; Lichtig et *al.*, 1999). The results from this study did not find any support that increases in non-RN staffing lead to

better patient outcomes. For ALOS and in-house mortality rate, the direction of the coefficient for this variable was opposite to what was hypothesized. This finding is somewhat related to previously published studies showing that increases in non-RN nursing staff relative to the RN staff were associated with poorer patient outcomes (Lichtig *et al.*, 1999; Needleman *et al.*, 2001). The results in this study may imply that increasing overall nursing staff through the addition of non-RN personnel does not necessarily improve patient outcomes and that possibly the substitution of RNs with non-RNs can potentially reduce the quality of patient outcomes.

Interaction Effect of RN and Non-RN Staffing

The results showed that the impact of RN staffing on patient outcomes was not moderated by the level of non-RN staffing. This study did not find support for the hypothesis that RNs and non-RNs were cospecialized or complementary assets and implies that the level of non-RN staffing relative to RN staffing in our population may not affect the impact of RNs on patient outcomes. This finding may not be surprising because military hospitals generally get nursing personnel based on some type of manpower standard. These manpower standards generally use a ratio of RNs to non-RN staff to calculate the number and type of nursing personnel a hospital will "earn." The nonsignificant findings in this area could be as a result of hospitals attempting to maintain a similar ratio of RN to non-RN staff.

However, it is logical to believe there most likely is a range in the staffing ratio between RNs and non-RNs that would reduce overall patient care costs without negatively impacting the quality of patient care provided. Clearly, there are numerous patient care tasks that can be performed by less trained nursing staff such as nurses

aides as good as or even better than RNs. The results of this study may imply that the staffing ratios between RNs and non-RNs in military hospitals are in a range that does not negatively impact, relative to one another, quality patient care. There may be a more optimal staffing ratio not seen in military hospitals that may be better at improving patient care.

Impact of Physician Staffing

The results of this study did not show any significant impacts between the amount of physician time spent with patients and any outcome measure: ALOS, in-house mortality rate, or 30-day readmission rate. The findings do not support the hypotheses that increasing the amount of time on patients spent by physicians would lead to lower ALOS, lower in-house mortality rate, or lower 30-day readmission rate. These hypotheses were developed from the hospitalist and intensivist streams of literature. Supporters of these care delivery models propose that better patient outcomes are a result of both better availability (to follow-up of test results, etc.) and concentrated care of inpatients and ICU patients (Grumbach and Fry, 1993; Peabody *et al.*, 1996; Wachter and Goldman, 1996). This study's findings may provide more support to the concentrated care of inpatients as the reason for better patient outcomes.

Another possible explanation for these results may be due to incomplete or inaccurate accounting of physician time spent on inpatient care. Because physicians have the ability to review testing results and other information from their offices and homes using a variety of telecommunication devices, physician time spent on these

activities may not be properly accounted for, potentially resulting in misleading results.

Other Findings

The study's findings showed that hospital Service (Air Force, Army, Navy) affiliation did not have a significant effect of patient outcomes. If Service affiliation is a proxy for culture, this implies that the "medical" culture may be more influential on military hospitals than Service specific cultures.

Bed size was found to have a significant direct effect on ALOS. A 100-bed increase in the size of a hospital would result in an increase of .4 days in ALOS. This may go against what would be expected. An increase in bed size may provide a hospital some economies of scale that improve the efficiency and efficacy of providing quality patient care that could potentially lead to a reduction in ALOS. On the other hand, bed size has a moderately sized positive indirect effect, through ALOS, on in-house mortality rate. In these cases, bed size may be another patient case-mix indicator as mentioned previously. Larger military hospitals care for more severely ill patients on average than smaller bedded facilities. This finding may imply that case-mix index may not be, by itself, adequately controlling for the differences in severity in patients being treated.

Further Research

The use of the RBV framework by researchers to date in examining the generation of a competitive advantage by hospitals through a unique set of internal resources has been very limited. Short *et al.* (2002: 14) believed that research in this

area is a "fruitful area of research for health care researchers who are interested in discovering what types of hospital resources lead to competitive advantage." Directions for future research can be viewed from examining the different types of resources that lead to a competitive advantage, the potentially different types of competitive advantage being generated, and, finally, the end results that the competitive advantage generates.

First, future research can focus on the different types of hospital resources that lead to better patient outcomes. From a staffing view, research can examine the effect of direct care paraprofessionals have on inpatient outcomes. Physical therapists' and pharmacists' involvement in inpatient care can, and most likely, impact patient outcomes. For example, a study performed at Walter Reed Army Medical Center in 1994 found patients that were treated by general medicine teams or surgical teams that contained a pharmacist experienced lower ALOS and lower cost per admission compared to patients being treated by teams without pharmacists. No differences in mortality rates were found (Bjornson *et al.*, 1994). Other hospital resources that may also be included in future research include the level of technological support available in the hospital, such as the availability of inpatient order entry, automated pharmacy dispensing systems, and level of diagnostic capabilities in the hospital.

Another resource that may impact the quality of patient care provided is the availability of telemedicine. With the rapid growth of broadband internet access, wireless communications, Wi-Fi, and other related telecommunications technology, the use of telemedicine capabilities has grown due to the decreasing cost and ease of use. Physicians can view x-rays, other diagnostic images, laboratory results, and other vital patient information from home and from many locations outside the hospital. This

capability may improve patient care by giving physicians the ability to diagnose and treat patients more rapidly and allowing them to follow a patient's progress more closely from wherever they are located.

Second, variables used to measure quality patient outcomes need to be expanded. The ones used in this study are just a few of a number of potential measures that may reflect quality patient outcomes. When examining the effect of nurse staffing on patients, Needleman *et al.* (2001) found 23 outcome measures that were impacted by nursing. Outcome measures of adverse events such as nosocomial infection rates, pharmaceutical administration errors, and patient falls are all potential measures of quality care. These outcome measures also have financial implications for a hospital. These types of adverse events can potentially lead to longer ALOS and malpractice claims.

Because hospitals need RNs to be able to provide quality care, one area that has received much attention recently deals with nurse burnout, satisfaction, and retention. The growing nursing shortage in many areas of the country has made the retention of nurses a top priority for many hospitals. Further research is needed to measure nurse burnout, satisfaction, and retention at military hospitals. Vahey, Aiken, Sloane, Clarke, and Vargas (2004) found that, in nursing units characterized as having adequate staff and good administrative support, nurses reported significantly lower burnout and higher levels of patient satisfaction with their care. Aiken *et al.* (2002) found that higher patient workloads led to higher job burnout and dissatisfaction among RNs. Forty-three percent of RNs who reported high burnout and job dissatisfaction intended to leave their current jobs within a year, compared to only 11% for nurses who did not report high levels of burnout and dissatisfaction. Specifically for military

nursing personnel, research is needed to assess the impact of deployments to places such as Iraq and Afghanistan for extended periods of time. Working in an extremely high stress environment may promote burnout more rapidly, potentially causing personnel to leave clinical care areas or leave the military altogether.

Finally, more research is needed to assess the impact of a hospital strategy of a competitive advantage based on quality has on other measures of hospital success, namely, cost and access. More detailed analysis is needed to examine what levels of quality patient care optimally balance financial performance, access to care, and any other measures a hospital considers essential in determining it is performing its mission. More integration between the strategy, nursing, physician, and balanced scorecard literature is needed to gain a more complete picture of the complex interrelationships involved in a hospital's long-term success and survival.

Limitations

Several limitations exist. The primary limitation is one of generalizability. The current study focused on military hospitals. Even though all military hospitals were included in the original sample, the two largest hospitals in terms of bed size were not used in any of the analyses because they were considered outliers. Further study is needed to see if the study's findings can apply to the DoD's largest hospitals.

As mentioned before, this study focused solely on military hospitals. Functional and cultural differences between civilian and military hospitals potentially limit the applicability of these findings to the civilian community. Further study that can better control for some of these differences is needed.

The choice in using RWPs in the calculation of case-mix index (based on RWPs) may also limit the ability of this study to find significant effects. Because RWP partitioning rules are based on similar costs rather than acuity of illness, they may not adequately capture much of the intrapatient severity differences. Because case-mix index in this study solely used administrative data for its calculation, it is subject to the criticism by many that its does not contain the clinical level data necessary to permit adequate adjustment of underlying patient conditions (Dans, 1993; Jollis *et al.*, 1993;). Future study using more clinically based case-mix indexes such as the Charlson Co-morbidity Index is needed to see if other significant relationships between inpatient staffing and patient outcomes exist.

Finally, the small sample size limits the ability of this study to find significant effects. Performing a future study at the ward level would increase the sample size and address this issue.

Conclusions

This study found some support for the main premise of the RBV: A firm's competitive advantage can be generated through the use of its internal resources. The current study did find some support that increasing nurse staffing, especially RN staffing, does lead to better inpatient quality outcomes as defined by ALOS and in-house mortality rate. Further research is needed to clarify more exactly what specific processes nurses are involved in that actually lead to lower ALOS and in-house mortality rates in military hospitals. This research did not find any significant relationships between physician staffing and any outcomes and between resources and 30-day readmission rates.

This study has contributed to the strategic management literature by being the second study to apply the RBV to hospitals. It has also expanded the nursing literature by not only examining the impacts of nursing staff on patient care in military settings but also providing a new model by which to evaluate these impacts. Using ALOS as a mediating variable between resources and in-house mortality rate appears to be a valid and potentially more revealing model compared to models that only examine direct effects of resources on outcomes such as in-house mortality rate. This study has also added to the physician and patient outcome literature, even though no significant relationships were found. It has provided some support that the benefits from the hospitalists and intensivists models of care may be more of a result of concentrated care of patients rather than increased availability. Results from this study have large potential implications. Each Service should reexamine their manpower standards that allocate RN and non-RN nursing staff. This study, along with previously published studies, suggests that increasing the number of RNs relative to the non-RN staff may be beneficial in lowering both ALOS and in-house mortality rate. It is hoped that the results of the proposed study will lead to more efficient and effective care being delivered to the military population.

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APPENDIX A

EMPIRICAL STUDIES USING THE RESOURCE BASED VIEW/THEORY

Empirical Studies Using the Resource Based View/Theory

Study	Sample/Industry	Independent Variables	Performance Variables	Methodology	Findings
Knott, 2003	Quick printing industry	Franchisee status, knowledge of routines, agreement of value of routines, and incentives to use routines. Control variables: age, size, equipment value, employee hours, total system sales, education, industry experience, management experience	Total returns	Ordinary least squares regression	Franchisees perform better than independent competitors. Routines accounted for a substantial portion of this superior performance. Knowledge of routines was the most important isolating mechanism that was associated with superior franchisee performance. Tacitness is not necessary for routine to hold value.
Adner and Helfat, 2003	30 companies in the US Petroleum Industry from 1977-1997	Dynamic managerial capabilities as measure by downsizing decisions	Return on Assets (ROA)	ANOVA and variance components estimation	Dynamic managerial capabilities were significant in explaining variance in firms' financial performance.
Short, Palmer, and Ketchen, 2002	85 hospitals from a large Metropolitan area between 1988-1992	Physical (capital investment), intangible (direct medical education costs), and financial resources (Debt to asset ratio), strategic groups, number of beds (control)	Financial performance (Return on assets), efficiency (average occupancy and admissions per bed)	Longitudinal analysis. Cluster analysis, MANOVA, multiple regression	Organizational resources were significantly related to return on assets (ROA), but not to efficiency variables. Group membership was related to efficiency measures but not to ROA. Group membership moderated the effect of organizational resources on admissions per bed only.

Empirical Studies Using the Resource Based View/Theory (Continued)

Study	Sample/Industry	Independent Variables	Performance Variables	Methodology	Findings
Schroeder, Bates, and Juntilla, 2002	164 manufacturing plants	Proprietary process and equipment, internal learning, and external learning	Manufacturing plant performance	Latent variable structural equation modeling	Internal and external learning drives the development of proprietary processes and equipment, which in turn is positively related to developing competitive advantage and measured by manufacturing plant performance.
Hitt, Bierman, Shimizu, and Kochhar, 2001	93 large U.S.law firms during 1987-1991	Human capital, leverage, service diversification, geographic diversification, and firm size (control)	Ratio of net income to total firm revenue	Generalized least squares regression	Human capital has a curvilinear, U-shaped, effect on performance. Leveraging human capital has a positive effect on performance.
Kraatz and Zajac, 2001	422 liberal arts colleges in the U.S.	Resource endowments (8 measures such as, human resources, financial assets, etc)	Strategic change (curriculum change) and performance (enrollment)	OLS regression, random effects model, discrete time-event history analysis	Colleges with greater resource endowments were less like to undertake strategic change This did not negatively affect performance, but maybe beneficial.

Empirical Studies Using the Resource Based View/Theory (Continued)

Study	Sample/Industry	Independent Variables	Performance Variables	Methodology	Findings
Pennings, Lee, and Witteloostuijn, 1998	Dutch accounting firms from 1880-1990	Human and social capital. Multiple control variables such as firm size and age	Firm dissolution	Discrete event history regression analysis	Human and social capital strongly predicted firm dissolution. Firm specific (versus industry specific) human capital and industry specific social capital was more predictive of firm survival.
Judge and Douglas, 1998	725 environmental executives from U.S. Based firms	Functional coverage, resources provided, environmental issues integration into the strategic planning process, and firm size (control)	Financial performance, environmental performance	Structural equation modeling	The amount of resources provided was positively associated with level of integration, functional integration was also positively related to level of integration, and the level of integration of environmental issues into the strategic planning process was positively related to financial and environmental performance.
Maijoor and Witteloostuijn, 1996	Complete Dutch audit market from 1967-1990	Law changes in accounting regulation	Number of accounts, registered accountants (RAs), income of RA partners, human capital, firms at the top	Descriptive data (means, standard deviations, etc)	The main predictions from RBV of the group and industry were confirmed. Large audit firms and their RA partners were able to utilize human capital (RAs) to earn economic rent.

Empirical Studies Using the Resource Based View/Theory (Continued)

Study	Sample/Industry	Independent Variables	Performance Variables	Methodology	Findings
Mehra, 1996	45 U.S. banks	10 key capabilities/skills which provide a competitive advantage in this industry used to determine strategic groups	Return on average asset, employee productivity, relative P/E ratio	Cluster analysis, MANOVA, ANOVA	Strategic (based on the 10 resource variables) groups were significantly different on all three performance measures. A strong association was found between firm resource endowments and superior performance.
Miller and Shamsie, 1996	Major U.S. film studios from 1936-1965	Property-based resources, knowledge-based resources	Financial performance	Correlations and autoregressive hetereoscedastic models	Property-based resources helped financial performance in stable environments, while knowledge-based resources help more in uncertain environments
Robins and Wiersema, 1995	120 manufacturing firms from the Fortune 500	Measures of a firms business portfolio relatedness, industry profitability, industry concentration, industry asset intensity, market share, and firm size	Return on Assets	Hierarchical multiple regression	Corporations with more highly related business portfolios (a potential measure of shared strategic assets) have better performance than firms with business portfolios that are not as related to each other.

Empirical Studies Using the Resource Based View/Theory (Continued)

Study	Sample/Industry	Independent Variables	Performance Variables	Methodology	Findings
Powell, 1995	CEO of firms with 50 or more employees in the northeastern U.S.	12 Total Quality Management (TQM) variables, industry control variables	Financial performance, TQM performance	Multiple regression	Results showed that traditional features of TQM, such as benchmarking, do not produce a competitive advantage. Certain tacit, behavioral, imperfectly imitable features such as open culture, employee empowerment, and executive commitment can produce advantage.
Henderson and Cockburn, 1994	10 major U.S. and European pharmaceutical companies	Component competence, architectural competence. Discovery (resources devoted to research), stock of discovery, scope, and therapeutic class were used as control variables.	Drug discovery productivity (number of patents)	ANOVA, poisson regression analysis	Results found strong support for "competence" as a source of competitive advantage in pharmaceutical research. Firm effects account for a substantial portion of the variance found in research productivity.
Mosakowski, 1993	86 entrepreneurial firms in the computer software industry	Strategic choice, size, total assets, and age were used as control variables	Sales revenues and net income performance	Two-staged least squares estimation	Certain resources and strategies associated with these resources lead to above-normal performance. Firms that adopted a focus or differentiation strategy were associated with higher performance

Empirical Studies Using the Resource Based View/Theory (Continued)

Study	Sample/Industry	Independent Variables	Performance Variables	Methodology	Findings
Collis, 1991	Global bearings industry	Core competence, organizational capability, administrative heritage	Firm strategy, financial performance, market share	Case studies	Using RBV along with an economic perspective are complementary and useful in explaining firm strategy choices and competitive outcomes.
Tallman, 1991	U.S. foreign auto industry from 1974-1985	Strategic groups, global sales, and ratio of U.S. sales to global sales (measure of strategic resource focus on the U.S. market)	Annual percentage increase in market share	Logistic regression and multiple regression	The support for the interaction of firm specific resources, strategy and structure to generate performance was found.
Hansen and Wernerfelt, 1989	60 Fortune 1000 firms	Economic factors (industry profitability, market share, firm size) and organizational factors (emphasis on human resources and emphasis on goal accomplishment	Five year average return on assets	Multiple regression	Economic and organizational factors are significant in determining fir performance. Organizational factors explain about twice as much variance as economic factors.

APPENDIX B

RESEARCH MODELS USED TO TEST HYPOTHESES

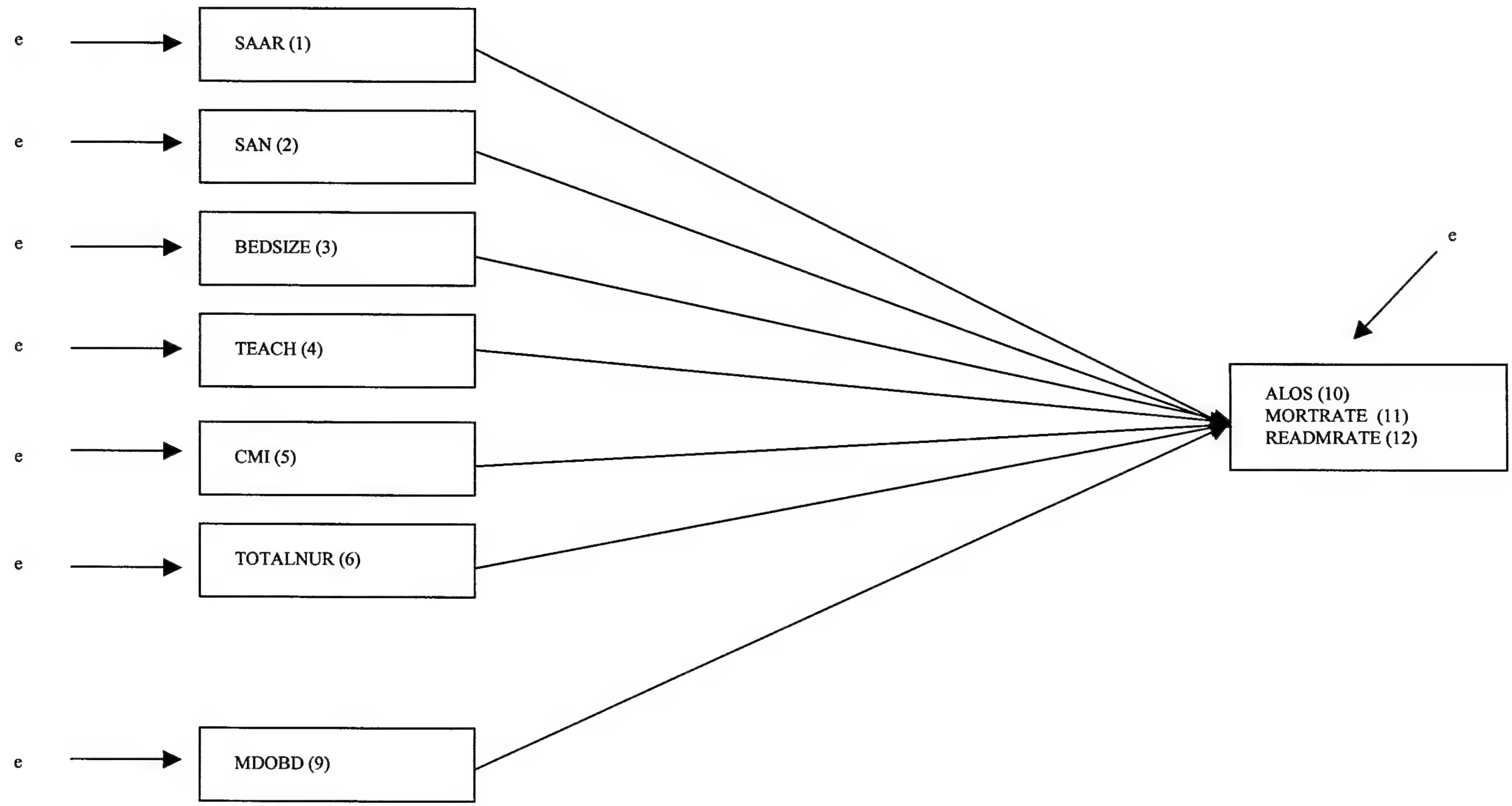

Figure B1. Research model 1 to test hypotheses 1a, 1b, and 1c

Note: The curved (double-arrowed) lines representing the correlations between the independent variables have been omitted for visual simplicity purposes. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

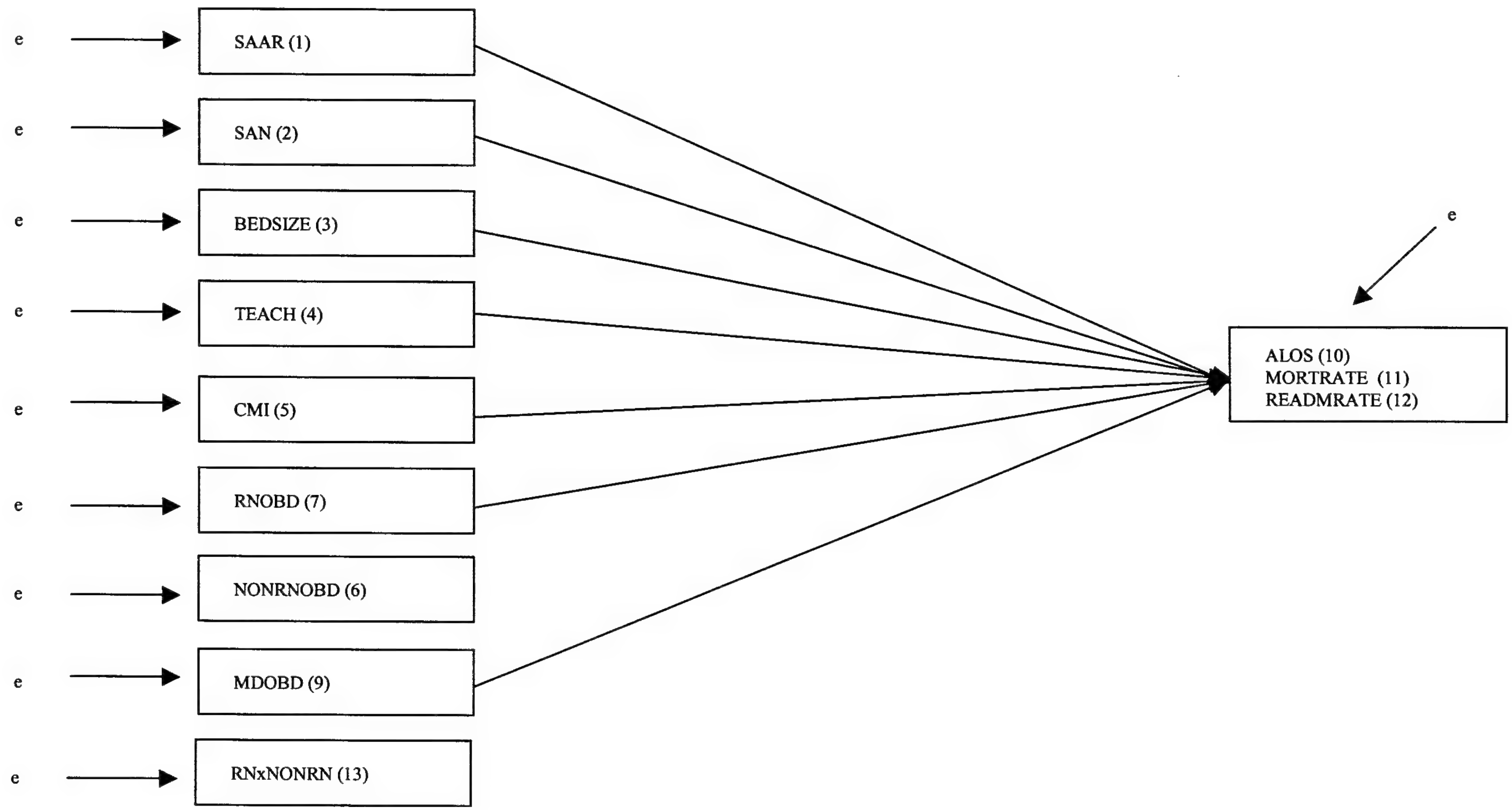

Figure B2. Research model 2 to test hypotheses 2a, 2b, 2c, 3a, 3b, 3c, 4a, 4b, 4c, 5a, 5b, and 5c

Note: The curved (double-arrowed) lines representing the correlations between the independent variables have been omitted for visual simplicity purposes. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, RNxNONRN is the interaction term representing the moderating effect of the non-RN staff on the RNs, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

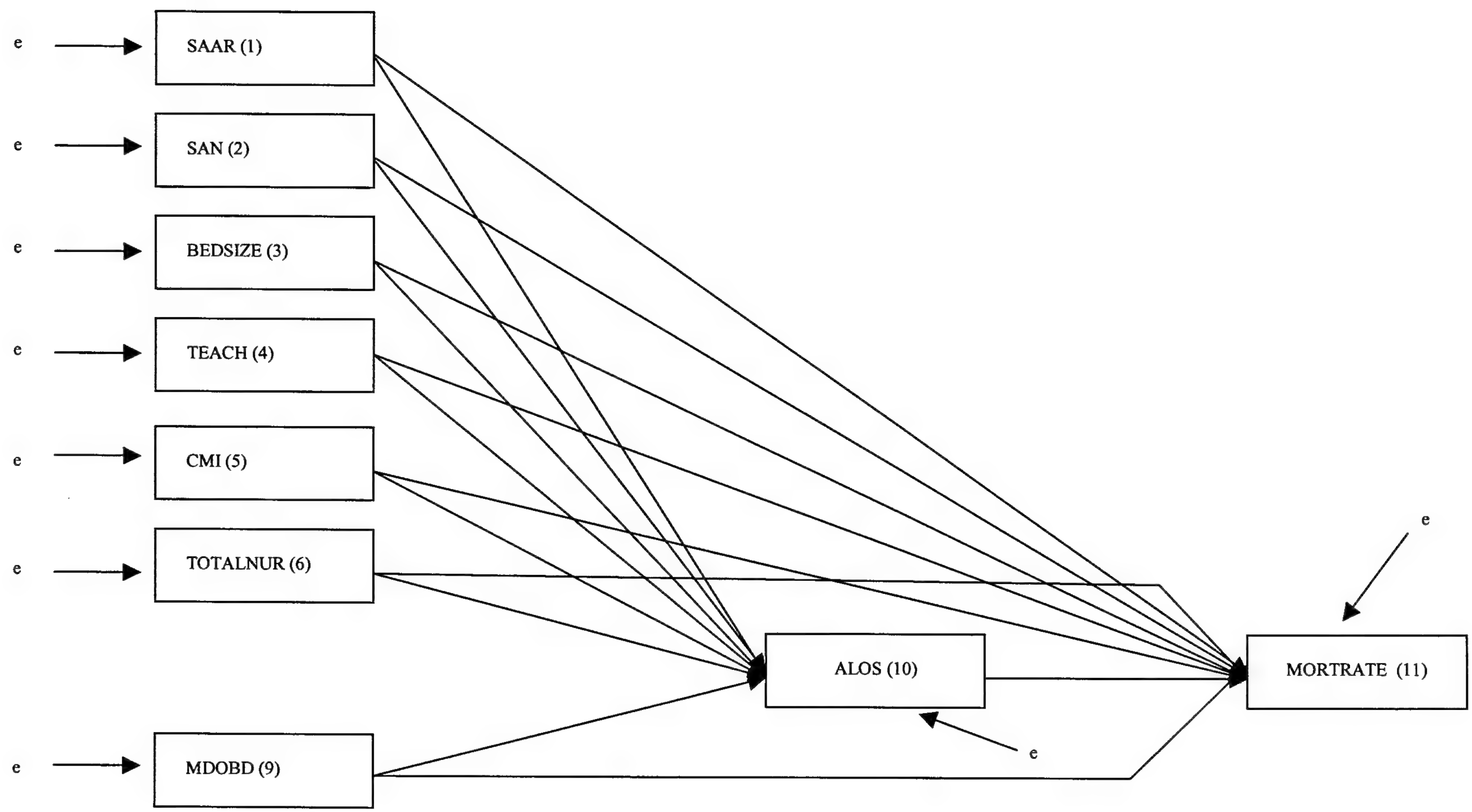

Figure B3. Research model 3 (path analysis model) to test hypotheses 6a

Note: The curved (double-arrowed) lines representing the correlations between the independent variables have been omitted for visual simplicity purposes. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, and MORTRATE is the in-house mortality rate.

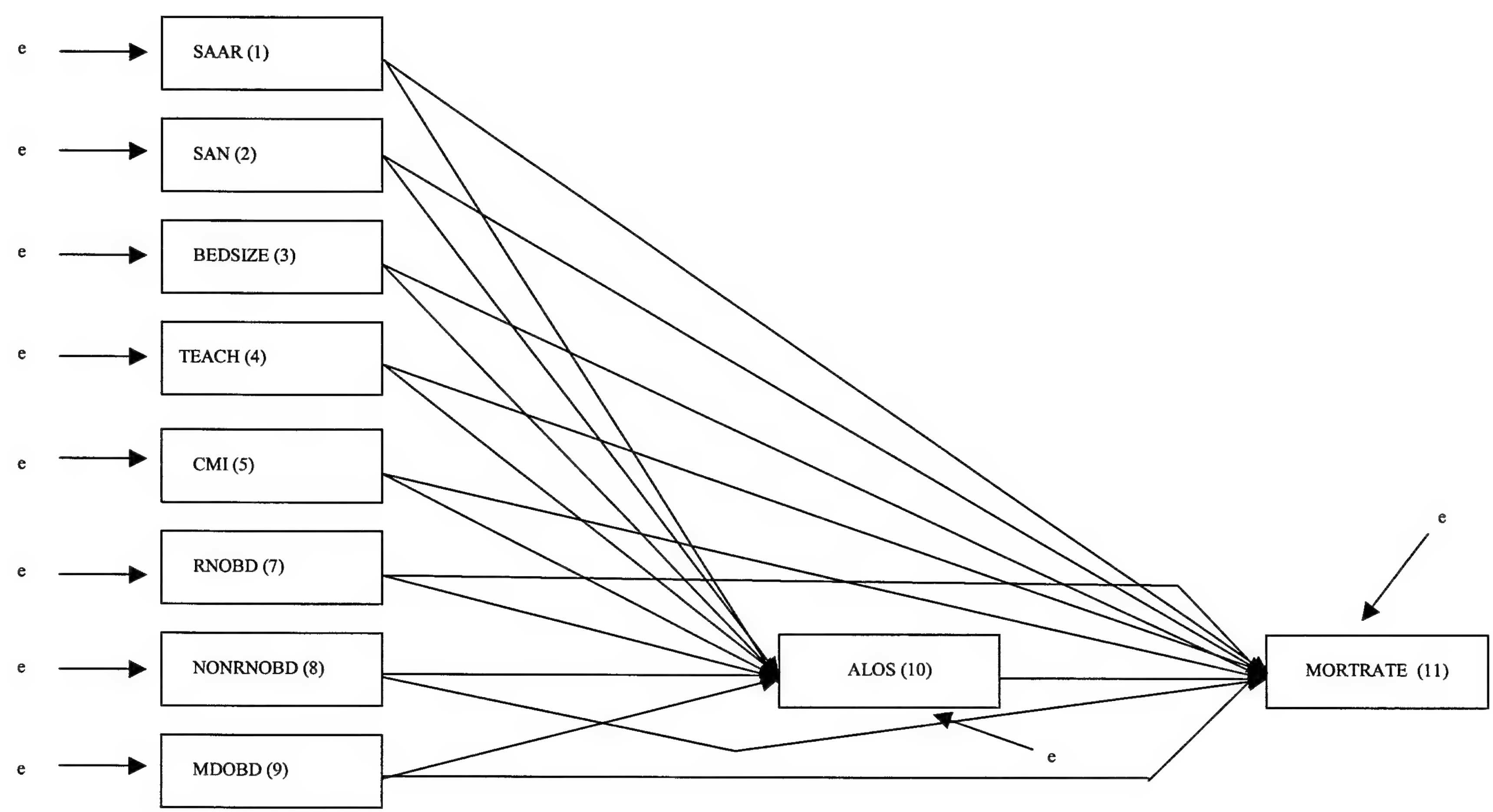

Figure B4. Research model 4 (path analysis model) to test hypotheses 6b

Note: The curved (double-arrowed) lines representing the correlations between the independent variables have been omitted for visual simplicity purposes. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, and MORTRATE is the in-house mortality rate.

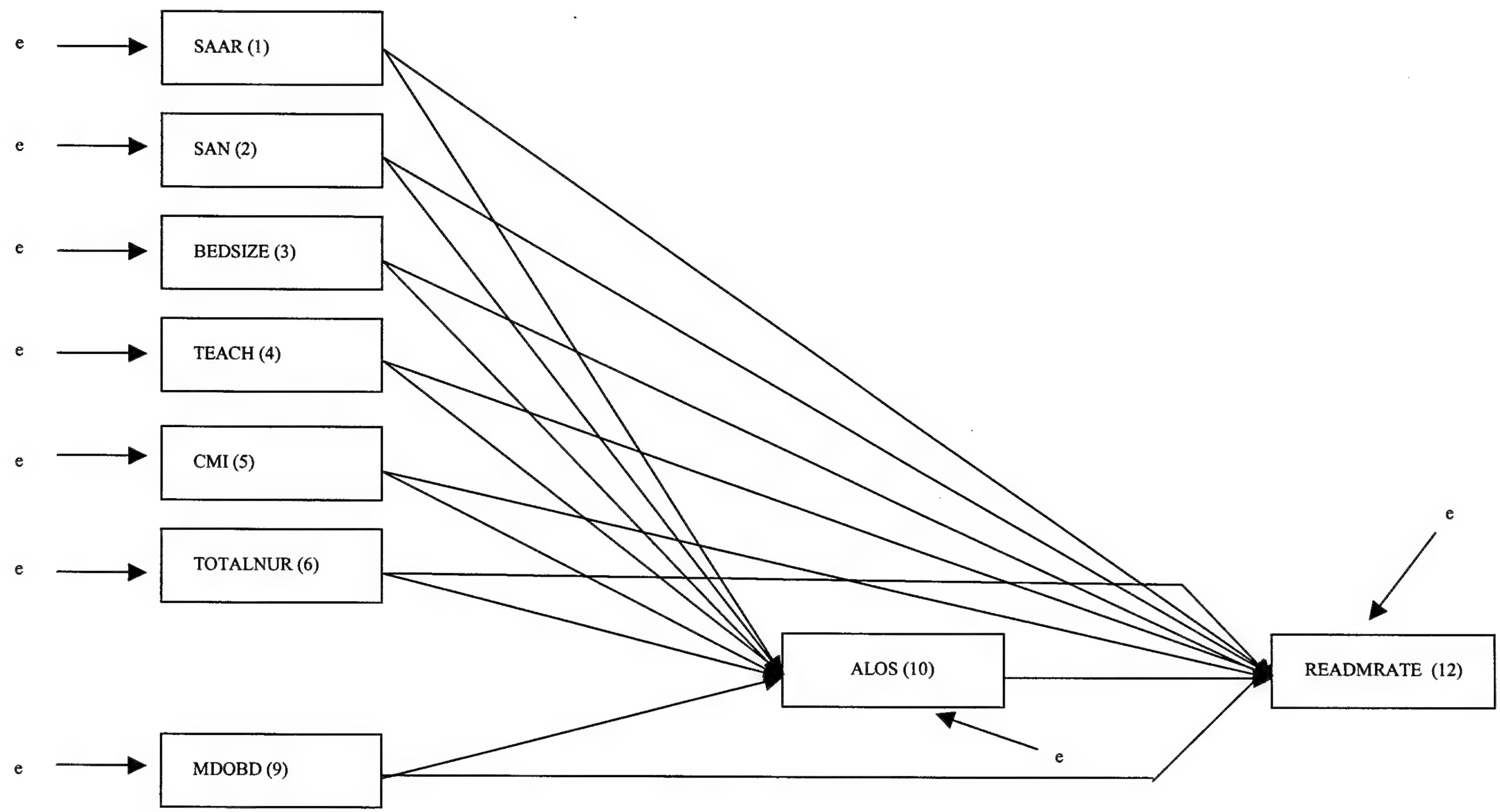

Figure B5. Research model 5 (path analysis model) to test hypotheses 7a

Note: The curved (double-arrowed) lines representing the correlations between the independent variables have been omitted for visual simplicity purposes. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, and READMRATE is the 30-day readmission rate.

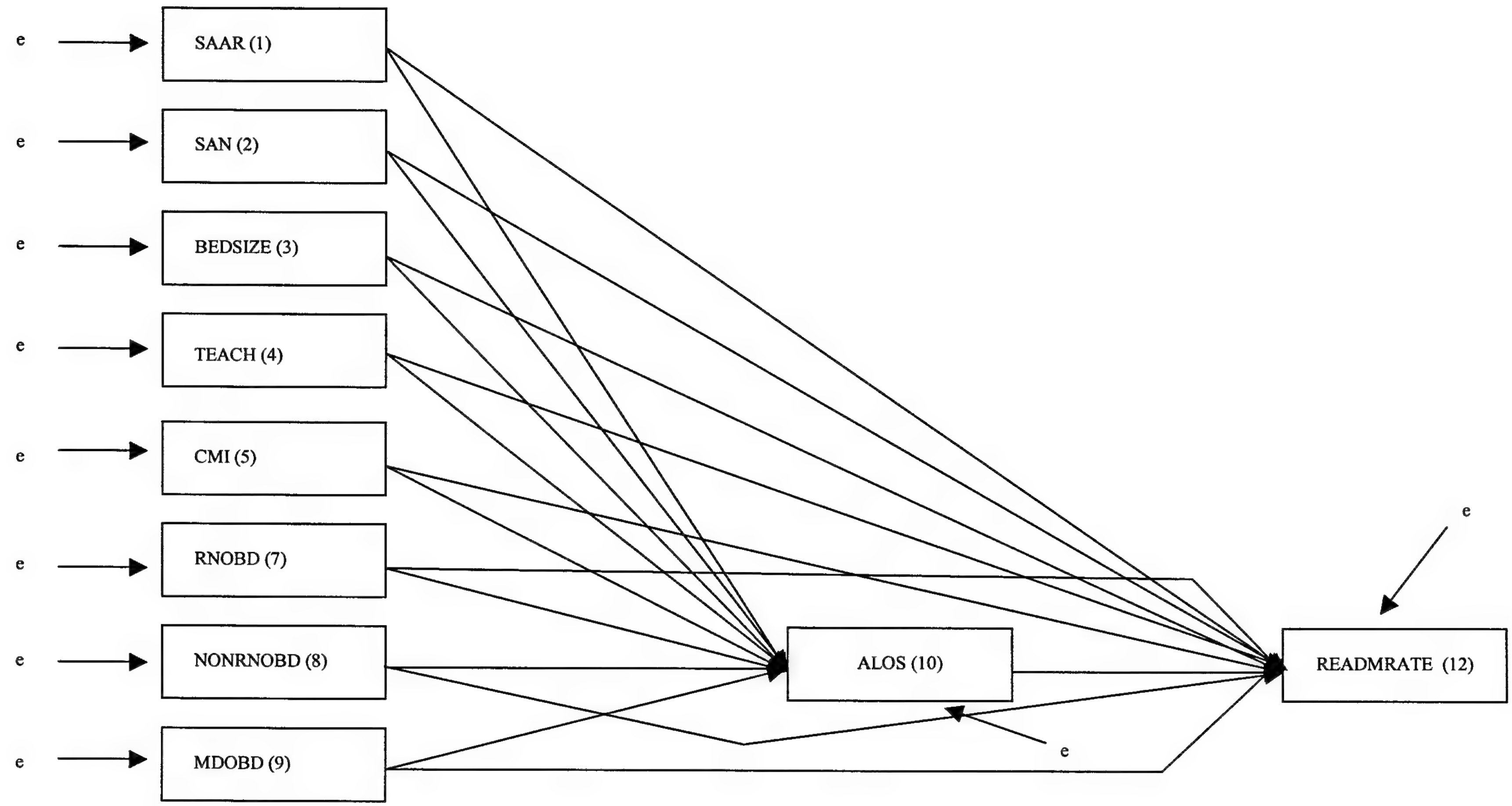

Figure B6. Research model 6 (path analysis model) to test hypotheses 7b

Note: The curved (double-arrowed) lines representing the correlations between the independent variables have been omitted for visual simplicity purposes. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, and READMRATE is the 30-day readmission rate.

APPENDIX C

LISTING OF THE 75 DoD MEDICAL TREATMENT FACILITIES

DMISID	Base / MTF Name	Service
3	FT RUCKER - LYSTER ACH	Army
5	FT WAINWRIGHT - BASSETT ACH	Army
32	FT CARSON - EVANS ACH	Army
37	WALTER REED AMC-WASHINGTON DC	Army
47	FT GORDON - EISENHOWER AMC	Army
48	FT BENNING - MARTIN ACH	Army
49	FT STEWART - WINN ACH	Army
52	TRIPLER AMC-FT SHAFTER	Army
57	FT RILEY - IRWIN ACH	Army
60	FT CAMPBELL - BLANCHFIELD ACH	Army
61	FT KNOX - IRELAND ACH	Army
64	FT POLK - BAYNE-JONES ACH	Army
75	FT LEONARD WOOD - L. WOOD ACH	Army
86	WEST POINT - KELLER ACH	Army
89	FT BRAGG - WOMACK AMC	Army
98	FT SILL - REYNOLDS ACH	Army
105	FT JACKSON - MONCRIEF ACH	Army
108	WILLIAM BEAUMONT AMC-FT. BLISS	Army
109	BROOKE AMC-FT. SAM HOUSTON	Army
110	FT HOOD - DARNALL ACH	Army
121	FT EUSTIS - MCDONALD ACH	Army
123	FT BELVOIR - DEWITT ACH	Army
125	MADIGAN AMC-FT. LEWIS	Army
131	FT IRWIN - WEED ACH	Army
606	HEIDELBERG MEDDAC	Army
607	LANDSTUHL REG MEDCEN	Army
609	WUERZBURG MEDDAC	Army
612	121ST GEN HOSP SEOUL	Army
6	ELMENDORF - 3RD MED GRP	Air Force
9	LUKE AFB - 56TH MED GRP	Air Force
14	TRAVIS AFB - 60TH MED GRP	Air Force
33	USAF ACADEMY - 10TH MED GROUP	Air Force
42	EGLIN AFB - 96TH MED GRP	Air Force
45	MACDILL AFB - 6TH MED GRP	Air Force
53	MT HOME AFB - 366TH MED GRP	Air Force
55	SCOTT AFB - 375TH MED GRP	Air Force
66	ANDREWS AFB - 89TH MED GRP	Air Force
73	KEESLER AFB - 81ST MED GRP	Air Force
78	OFFUTT AFB - 55TH MED GRP	Air Force

DMISID	Base / MTF Name	Service
79	NELLIS AFB - 99TH MED GRP	Air Force
95	WRIGHT PATTERSON - 74TH MED GRP	Air Force
101	SHAW AFB - 20TH MED GRP	Air Force
113	SHEPPARD AFB - 82ND MED GRP	Air Force
117	WILFORD HALL - 59TH MED WING, LACKLAND	Air Force
120	LANGLEY AFB - 1ST MED GRP	Air Force
633	LAKENHEATH - 48TH MED GRP	Air Force
635	INCIRLIK - 39TH MED GRP	Air Force
638	OSAN AB - 51ST MED GRP	Air Force
639	MISAWA - 35TH MED GRP	Air Force
640	YOKOTA AB - 374TH MED GRP	Air Force
805	SPANGDAHLEM - 52ND MED GROUP	Air Force
808	AVIANO - 31ST MED GRP	Air Force
24	NH CAMP PENDLETON	Navy
28	NH LEMOORE	Navy
29	NMC SAN DIEGO	Navy
30	NH TWENTYNINE PALMS	Navy
38	NH PENSACOLA	Navy
39	NH JACKSONVILLE	Navy
56	NH GREAT LAKES	Navy
67	NNMC BETHESDA	Navy
91	NH CAMP LEJEUNE	Navy
92	NH CHERRY POINT	Navy
104	NH BEAUFORT	Navy
124	NMC PORTSMOUTH	Navy
126	NH BREMERTON	Navy
127	NH OAK HARBOR	Navy
615	NH GUANTANAMO BAY	Navy
616	NH ROOSEVELT ROADS-CEIBA	Navy
617	NH NAPLES	Navy
618	NH ROTA	Navy
620	NH GUAM-AGANA	Navy
621	NH OKINAWA	Navy
622	NH YOKOSUKA	Navy
623	NH KEFLAVIK	Navy
624	NH SIGONELLA	Navy

APPENDIX D

BIVARIATE CORRELATIONS AND DESCRIPTIVE STATISTICS FOR MODELS USED TO TEST HYPOTHESES

	n	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12
Control Variables															
1. SAAR	70	.37	.49	1											
2. SAN	70	.31	.47	-.52**	1										
3. BEDSIZE	70	58.97	53.66	.32**	.00	1									
4. TEACH	70	.33	.47	.09	-.08	.57**	1								
5. CMI	70	.72	.23	.17	-.14	.54**	.45**	1							
Predictor Variables															
6. TOTALNUR	70	1177.47	558.64	-.50**	.26*	-.59**	-.42**	-.32**	1						
7. RNOBD	70	553.71	250.52	-.39**	.13	-.64**	-.46**	-.37**	.96**	1					
8. NONRDOBD	70	623.76	327.93	-.56**	.35**	-.52**	-.37**	-.27*	.97**	.86**	1				
9. MDOBD	70	107.96	58.25	-.09	.10	.17	.40**	.15	-.04	-.07	-.03	1			
Dependent Variables															
10. ALOS	70	2.80	.77	.20	-.11	.65**	.38**	.74**	-.50**	-.56**	-.42**	-.02	1		
11. MORTRATE	70	.39	.55	.11	-.05	.53**	.47**	.73**	-.34**	-.40**	-.27*	.20	.66**	1	
12. READMRATE	70	9.74	3.10	-.12	.05	.20	.16	.33**	.01	.01	.02	.17	.15	.17	1

Figure D1. Bivariate correlations and descriptive statistics for models used to test hypotheses 1a, 2a, 3a, 4a

Note: * Significant at the $p \leq 0.05$ level (2-tailed), ** Significant at the $p \leq 0.01$ level (2-tailed). Facilities excluded from the sample: Portsmouth Naval Base, Lackland AFB, Fort Rucker, Travis AFB, and Washington DC (Walter Reed Army Medical Center). SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

	n	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12
Control Variables															
1. SAAR	69	.38	.49	1											
2. SAN	69	.30	.46	-.51**	1										
3. BEDSIZE	69	60.29	57.08	.32**	-.01	1									
4. TEACH	69	.33	.47	.09	-.07	.56**	1								
5. CMI	69	.72	.23	.17	-.15	.58**	.45**	1							
Predictor Variables															
6. TOTALNUR	69	1175.75	563.15	-.51**	.27*	-.58**	-.43**	-.33**	1						
7. RNOBD	69	553.34	252.17	-.39**	.13	-.62**	-.46**	-.37**	.96**	1					
8. NONRDOBD	69	622.41	330.81	-.56**	.35**	-.52**	-.37**	-.28*	.97*	.86**	1				
9. MDOBD	69	106.67	59.32	-.12	.11	.09	.36**	.08	-.02	-.04	-.01	1			
Dependent Variables															
10. ALOS	69	2.82	.85	.22	-.12	.69**	.38**	.76**	-.48**	-.54**	-.41**	-.10	1		
11. MORTRATE	69	.35	.46	.13	-.12	.60**	.56**	.75**	-.39**	-.45**	-.32*	.18	.71**	1	
12. READMRATE	69	9.70	3.11	-.11	.03	.21	.17	.33**	.01	.01	.01	.15	.16	.13	1

Figure D2. Bivariate correlations and descriptive statistics for models used to test hypotheses 1b, 2b, 3b, 4b

Note: * Significant at the $p \leq 0.05$ level (2-tailed), ** Significant at the $p \leq 0.01$ level (2-tailed). Facilities excluded from the sample: Portsmouth Naval Base, Lackland AFB, Fort Rucker, Travis AFB, Agana, and Fort Sam Houston. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

	n	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12
Control Variables															
1. SAAR	70	.39	.49	1											
2. SAN	70	.31	.47	-.54**	1										
3. BEDSIZE	70	62.30	58.70	.35**	-.04	1									
4. TEACH	70	.34	.48	.11	-.10	.58**	1								
5. CMI	70	.73	.25	.21	-.17	.61**	.47**	1							
Predictor Variables															
6. TOTALNUR	70	1165.00	561.17	-.51**	.28*	-.58**	-.43**	-.34**	1						
7. RNOBD	70	547.24	251.65	-.40**	.15	-.63**	-.47**	-.39**	.96**	1					
8. NONRDOBD	70	617.76	329.21	-.56**	.36**	-.52**	-.38**	-.28*	.97**	.86**	1				
9. MDOBD	70	107.58	58.64	-.13	.10	.09	.36**	.08	-.02	-.04	-.01	1			
Dependent Variables															
10. ALOS	70	2.86	.88	.25*	-.14	.71**	.40**	.78**	-.49**	-.55**	-.42**	-.10	1		
11. MORTRATE	70	.41	.56	.13	-.07	.57**	.49**	.75**	-.35**	-.41**	-.28*	.15	.68**	1	
12. READMRATE	70	9.59	2.71	-.06	.09	.29*	.25*	.40**	-.04	-.06	-.02	.23	.26*	.27*	1

Figure D3. Bivariate correlations and descriptive statistics for models used to test hypotheses 1c, 2c, 3c, and 4c

Note: * Significant at the $p \leq 0.05$ level (2-tailed), ** Significant at the $p \leq 0.01$ level (2-tailed). Facilities excluded from the sample: Portsmouth Naval Base, Lackland AFB, Washington D.C. (Walter Reed Army Medical Center), Fort Rucker, Travis AFB, Agana, and Fort Sam Houston. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

	n	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12
Control Variables															
1. SAAR	68	.37	.49	1											
2. SAN	68	.31	.47	-.51**	1										
3. BEDSIZE	68	57.34	51.92	.29*	.03	1									
4. TEACH	68	.32	.47	.06	-.05	.55**	1								
5. CMI	68	.71	.21	.12	-.13	.48**	.43**	1							
Predictor Variables															
6. TOTALNUR	68	1183.88	563.24	-.50**	.26*	-.59**	-.41**	-.31*	1						
7. RNOBD	68	557.34	251.83	-.38**	.12	-.63**	-.45**	-.35**	.96**	1					
8. NONRDOBD	68	626.54	331.47	-.55**	.35**	-.52**	-.36**	-.26*	.97**	.86**	1				
9. MDOBD	68	107.74	59.09	-.10	.10	.18	.40**	.16	-.04	-.06	-.02	1			
Dependent Variables															
10. ALOS	68	2.77	.74	.16	-.09	.61**	.35**	.70**	-.49**	-.55**	-.42**	-.03	1		
11. MORTRATE	68	.33	.44	.09	-.10	.54**	.55**	.71**	-.37**	-.43**	-.30*	.24	.68**	1	
12. READMRATE	68	9.66	3.11	-.13	.04	.18	.15	.31**	.02	.02	.03	.17	.13	.11	1

Figure D4. Bivariate correlations and descriptive statistics for models used to test hypothesis 6a and 6b

Note: * Significant at the $p \leq 0.05$ level (2-tailed), ** Significant at the $p \leq 0.01$ level (2-tailed). Facilities excluded from the sample: Portsmouth Naval Base, Lackland AFB, Washington D.C. (Walter Reed Army Medical Center), Fort Rucker, Travis AFB, Agana, and Fort Sam Houston. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

	n	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12
Control Variables															
1. SAAR	69	.38	.49	1											
2. SAN	69	.32	.47	-.53**	1										
3. BEDSIZE	69	59.42	53.92	.32**	-.01	1									
4. TEACH	69	.33	.47	.09	-.09	.57**	1								
5. CMI	69	.72	.24	.17	-.15	.54**	.45**	1							
Predictor Variables															
6. TOTALNUR	69	1172.86	561.39	-.50**	.272*	-.59**	-.42**	-.32**	1						
7. RNOBD	69	551.10	251.40	-.39**	.14	-.63**	-.46**	-.37**	.96**	1					
8. NONRDOBD	69	621.76	329.90	-.56**	.36**	-.52**	-.37**	-.27*	.97**	.86**	1				
9. MDOBD	69	108.64	58.39	-.10	.09	.17	.39**	.15	-.04	-.06	-.02	1			
Dependent Variables															
10. ALOS	69	2.81	.78	.20	-.12	.65**	.37**	.74**	-.50**	-.56**	-.42**	-.03	1		
11. MORTRATE	69	.39	.55	.10	-.06	.53**	.47**	.73**	-.33**	-.39**	-.27*	.20	.66**	1	
12. READMRATE	69	9.55	2.71	-.08	.10	.27*	.23	.39**	-.02	-.04	-.01	.26*	.22	.25*	1

Figure D5. Bivariate correlations and descriptive statistics for models used to test hypothesis 7a and 7b

Note: * Significant at the $p \leq 0.05$ level (2-tailed), ** Significant at the $p \leq 0.01$ level (2-tailed). Facilities excluded from the sample: Portsmouth Naval Base, Lackland AFB, Washington D.C. (Walter Reed Army Medical Center), Fort Rucker, and Travis AFB. SAAR is hospital Service affiliation (1 = Army, 0 = all others), SAN is hospital Service affiliation (1 = Navy, 0 = all others), BEDSIZE is the number of operating beds in the hospital, TEACH is the teaching status of the hospital (0 = no graduate medical education present, 1 = graduate medical education present), CMI is the case-mix index, TOTALNUR is the average amount of time spent by the total nursing staff per OBD, RNOBD is the average amount of time spent by a RN per OBD, NONRNOBD is the average amount of time spent by the non-RN staff per OBD, MDOBD is the average amount of time spent by a physician per OBD, ALOS is the average length of stay, MORTRATE is the in-house mortality rate, and READMRATE is the 30-day readmission rate.

APPENDIX E

THE UNIVERSITY OF ALABAMA AT BIRMINGHAM INSTITUTIONAL REVIEW BOARD APPROVAL FORM

THE UNIVERSITY OF
ALABAMA AT BIRMINGHAM

Institutional Review Board for Human Use

Form 4: IRB Approval Form
Identification and Certification of Research
Projects Involving Human Subjects

UAB's Institutional Review Boards for Human Use (IRBs) have an approved Federalwide Assurance with the Office of Human Research Protections (OHRP). The UAB IRBs are also in compliance with 21 CFR Parts 50 and 56 and ICH GCP Guidelines. The Assurance became effective on November 24, 2003 and the approval period is for three years. The Assurance number is FWA00005960.

Principal Investigator: YAP, GLENN

Co-Investigator(s):

Protocol Number: **E040405001**

Protocol Title: *Staffing Levels and Inpatient Outcomes at Military Health Care Facilities: A Resource-Based View*

The above project was reviewed on 4/15/04. The review was conducted in accordance with UAB's Assurance of Compliance approved by the Department of Health and Human Services. This project qualifies as an exemption as defined in 45CF46.101, paragraph 4.

This project received EXEMPT review.

IRB Approval Date: 04/15/04

Date IRB Approval Issued: 04/15/04

Sheila Moore, CIP

Sheila Moore, CIP
Director, Office of the Institutional
Review Board for Human Use (IRB)

Investigators please note:

IRB approval is given for one year unless otherwise noted. For projects subject to annual review research activities may not continue past the one year anniversary of the IRB approval date.

Any modifications in the study methodology, protocol and/or consent form must be submitted for review and approval to the IRB prior to implementation.

Adverse Events and/or unanticipated risks to subjects or others at UAB or other participating institutions must be reported promptly to the IRB.